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Intergenerational Effects of Trade Liberalization

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Abstract

2002 Pew Global Attitudes survey shows that workers' support for free trade decreases with age. The relation between age and supporting free trade is a phenomenon previously unexplored by economists. We study distributional effects of trade liberalization, in particular age and gains from free trade, using a dynamic structural general equilibrium model. The method we use here is *complimentary to* Artuc, Chaudhuri and McLaren (forthcoming), and can handle a much richer treatment of ex-ante, endogenous and unobserved worker heterogeneity. This more efficient method allows us to calculate distributional effects of trade liberalization in detail but it requires a completely different estimation strategy, which comes at a cost of more computation time and stronger assumptions on workers' expectations. After estimating the structural model with U.S. data sets NLSY and CPS, we simulate a hypothetical trade liberalization in metal manufacturing sector (which has been especially vulnerable to trade shocks in the past, the steel industry in particular). We show gradual adjustment of labor allocation, wages and prices in response to this trade shock. We find a "mirror effect"where very young workers in the metal sector are moderately worse off and older workers are extremely worse off, while young workers in manufacturing sector are moderately better off and older workers are extremely better off.

JEL Classification: F1, D58, J2, J6

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1 Introduction

Recently, trade economists have developed dynamic structural models to analyze effects of trade liberalization. Only a few of those structural models were designed to analyze welfare effects of free trade on workers, while many of them, especially those which generated a large body of reasearch, focused on firms rather than workers.[2] Most of the research on distributional effects of trade liberalization on workers have been conducted via reduced form regressions.[3] Although reduced form regressions helped economists to answer many questions about effects of trade policy shocks, there are certain very interesting questions that can not be answered by them, such as: How long will it take to reach the new steady state after a trade shock? What are the welfare effects on export-sector workers? How do workers adjust to free trade in case of delayed trade liberalization - if it is not implemented yet? What are the non-pecuniary welfare costs of trade liberalization? Artuc, Chaudhuri and McLaren (Forthcoming) developed a method to answer such questions (henceforth ACM), within a dynamic structural general-equilibrium framework.[4] The theoretical foundation of ACM was introduced by Cameron, Chaudhuri and McLaren (2008). Although ACM's method was well suited to analyze welfare effects of trade liberalization, it was not designed to study distributional effects in detail. Studying distributional effects seriously requires extremely large data sets, when detailed worker heterogeneity is introduced to their model. This is because their estimation strategy relies on aggregate mobility matrices for each observed worker type, which could easily be contaminated with empty cells if the state-space is finely partitioned.

In this paper, we develop a different method, complementary to ACM, which can be used to study distributional effects of trade liberalization at a cost of longer computation time and stronger assumptions on workers' expectations. The model we introduce in this paper is also inspired from Cameron, Chaudhuri and McLaren (2008) similar to ACM, but the main difference is we do not use their (computationally cheap and compact) Euler-equation condition approach. Instead, we calculate expected values of workers similar to structural discrete choice models in the labor economics literature, which allows us to introduce a richer

[2]Such as Bernard, Eaton, Jensen and Kortum (2003) and Melitz (2003).

[3]Among others, some prominent examples are Revenga (1992), Pavcnik, Goldberg and Attanasio (2004) and Kletzer (2002). See Slaughter (1998) for an overview.

[4]Among others, we can list Davidson and Matusz (2001), Ritter (2009), Helpman and Itskhoki (2009) and Kambourov (2003) as examples of structural trade models with a special emphasis on labor.

treatment of ex-ante and endogenous worker heterogeneity compared to ACM. With the introduction of ex-ante and endogenous worker heterogeneity (age, education and experience), we can analyze distributional effects of trade liberalization in more detail in addition to dynamics of the adjustment process. Another difference is, we use NLSY data set along with CPS, which provides detailed work history. Using work history of workers, we model human capital accumulation process joint with sectoral mobility. By doing so, we can calculate welfare loss of import competing sector workers, who lose their sector specific human capital as their sector shrinks, and welfare gains of exporting sector workers at the same time. The final major difference is the sector opening to free trade, in contrast to their analysis on the manufacturing sector, we focus on liberalization in the metal manufacturing sector. Since metal manufacturing output is not directly consumed, it has no effect on consumer price index. Therefore, we have to allow outputs of sectors to be used as inputs in the production function (otherwise free trade of metal manufacturing product would not directly affect other sectors). Studying a very small sector, such as metal manufacturing, with ACM's method would require an unreasonably large data set even without worker heterogeneity. [5]

In this paper, we will particularly focus on effects of trade liberalization on different generations. Recent Pew Global Attitudes survey, conducted in 2002, showed that young people are more enthusiastic about free trade compared to older people. The negative correlation between age and support for free trade is previously unexplored by economists. Without considering any economic explanation, one could attribute this negative correlation (between age and supporting free trade), to older people's being more comfortable with status-quo compared to young. In other fields of social sciences, there are studies analyzing age and openness to change, among others Na and Duckitt (2003) report that young Koreans are more open to change compared to old. Taking those and other researchers seriously, one can claim that older people's being more conservative can potentially explain their attitude towards free trade. However, we show that there is indeed an economic explanation as well for this intriguing difference between young and old workers, although it was unnoticed so far by economists. We do not deny the possibility of existance of psychological factors, which are out of the scople of this paper.

Imagine that all workers were perfectly mobile across sectors, then all workers would be

[5]Needless to say that their method also has some other advantages over ours. For example, it requires shorter time series since their method does not rely on calculation of future values.

unanimously better off or worse off after trade liberalization, as in Heckscher-Ohlin model. If all workers were absolutely immobile and attached to certain sectors, then there would be clearly distinct winners and losers from free trade; in that case, workers' sectors would determine their gain and loss. In reality, mobility costs probably lie between these two extremes and vary across groups. A major source of variation in mobility has to do with the age of affected workers, causing differences in their position towards free trade.

In order to explore the relation between worker mobility, age and welfare effects of free trade, we first estimate human capital accumulation process and mobility of workers jointly with a sectoral choice model, using NLSY and CPS data. Then, we calibrate production, input demand and consumption demand functions to set a general equilibrium framework with the estimated sectoral choice parameters. Finally, we simulate a hypothetical trade liberalization in the metal manufacturing sector (which has been especially vulnerable to trade shocks in the past, the steel industry in particular) to analyze gradual adjustment of labor, wages and prices in all sectors in response to this trade shock. The trade shock can be considered simply as an exogenous reduction in the metal manufacturing product's price, as cheaper imports will be available with trade liberalization; everything else will be endogenous.

It should be noted that, although we put a special emphasis on human capital accumulation process, our ultimate goal is to simulate trade shocks, which will make our model different from similar research in labor literature such as Keane and Wolpin (1997) and Lee and Wolpin (2004). We are borrowing some insights from sectoral/occupational choice literature to analyze a topic which can not be explored with other international trade economics tools. We deviate from them by modeling sectoral choice rather than occupational and educational choice, since a trade shock first hits sectors, then possibly occupations in a less direct way. Analyzing effects of trade liberalization on occupations is out of the scope of this paper, and left for future research. In addition to this deviation, we reduced the state space by using a limited number of age, education and experience groups, so that the counterfactual simulations are computationally feasible. This simplification decreases the computational burden significantly by reducing the time needed to calculate value functions, which makes our model relatively easy to implement compared to other longitudinal-structural models. Since we have endogenous wages and multiple sectors, most of the models developed by labor economists would not be computationally feasible for our purpose. Finally, we have included idiosyncratic utility shocks in addition to wage shocks, similar to Sullivan (2004) and ACM. Inclusion of these shocks is necessary because deviations in wages can only explain a very small part of labor mobility, see two papers mentioned earlier for more discussion.

One important question is: Why old workers are less mobile than young workers? Following the previous literature we can give several different answers to this question: For example Borjas and Rosen (1980), attributed decreases in mobility with age to increases in wages with tenure. The decrease in mobility with age can be attributed to specific human capital as in Topel (1991), better job match as in Jovanovic (1979) or implicit contracts as in Lazear (1979). Groot and Verberne (1997) suggested that the decrease in mobility with age can be partially attributed to non-financial reasons as well. Unfortunately, we will not be able to incorporate all these features in our model at the same time: we assume that workers become less mobile as they get older because they become more likely to hold sector specific human capital and the other reasons will be captured by their implicit moving cost a la Groot and Verberne (1997). Although models of sector specific human capital is less common in the literature compared to firm specific human capital; Neal (1995) shows that it is a very important part of human capital.

Another related line of research to ours is the displaced workers literature, such as Jacobson, LaLonde and Sullivan (1993). Although they also analyze distributional effects of trade liberalization, their analysis is focused on import competing sector workers only. They study only import-competing sector workers with a natural experiment, therefore their results can be considered as more precise, however they can not explain what will happen in a hypothetical scenario and what will happen in other sectors, such as service.

In the next section we will present the model, followed by estimation results. After a section on counterfactual simulation of trade liberalization in metal sector, we will introduce unobserved heterogeneity to the model. Then we will conclude the paper.

2 Model

Consider an economy with I industries, where workers choose a sector to work *dynamically* in each period. Aggregate production functions for each sector has a Cobb-Douglas form, where workers' wages are marginal product of labor derived from the production functions. Workers preferences are also expressed with Cobb-Douglas utility functions. Our goal is to simulate a hypothetical trade liberalization in one of the sectors (metal manufacturing) and see how labor allocations, prices, wages and option values adjust after the trade shock. We will discuss welfare effects of this policy change on workers from different age, education and experience groups. The parameters of the workers' problem are estimated from NLSY79 and CPS, while the parameters of the production functions are calibrated from BEA data.

The industries are aggregated into 4 main sectors: 1. "Manuf": Manufacturing and Agriculture (tradable sector), 2. "Metal": Metal Manufacturing (sector subject to policy change) 3. "Service": Service except Trade (non-tradable sector) 4. "Trade": Wholesale and retail trade (another non-tradable sector). The industries are aggregated mainly in two groups, tradeable and non-tradeables. However, since "wholesale and retail trade" is a very large industry, we decided to take it as a separate sector apart from service.[6]

In the next sub-section we will describe workers' problem.

2.1 Workers

Assume that there are N workers and I sectors in the economy. Workers choose a sector in which to work in each period. If a worker indexed by n decides to work in sector i then $d_t^n = i$ where

$$d_t^n \in \{1, 2, 3, 4\}. \tag{1}$$

A worker, n, receives wage w_t^{ni} from working in sector i. Wage of worker n is defined as the price of sector specific human capital, r_t^i, times units of human capital hold by the individual, h_t^{ni}:

$$w_t^{ni} = r_t^i h_t^{ni},$$

[6]A more favorable approach is to use two digit definitions to separate industries which have different characteristics than the others such as Agriculture, Professional, Government, and to include occupational choice as well. There are two reasons that prevent us from doing so: First, Increasing number of choices will make the problem computationally infeasible. Second, the main dataset we use, NLSY79, has a fairly small sample size, especially for metal workers, therefore estimates of important sector specific parameters would not be significant.

where units of human capital is defined as

$$\log h_t^{ni} = \phi_0^i + \phi_1^i Coll^n + \phi_2^i SecEx_t^{ni} + \phi_3^i MktEx_t^n + \phi_4 Coll^n SecEx_t^{ni} + \phi_5 Coll^n MktEx_t^n + z_t^{ni}, \tag{2}$$

where $Coll^n$ is a dummy for college education, $SecEx_t^{ni}$ is years of sectoral experience in sector i, $MktEx_t^n$ is years of market experience and z_t^{ni} is an iid normal random shock. Since we are interested in fluctuations in r_t^i, we will not derive the standard Mincer wage equation from this specification but rather move in a slightly different direction. For convenience, let us define $\log h_t^{ni} = \phi_0^i + X_t^{ni}\Phi^i + z_t^{ni}$, where X_t^{ni} is a vector of individual characteristics, Φ^i is a vector of sector specific human capital parameters except the intercept ϕ_0^i. We can write wages as a function of average wages:

$$\begin{aligned} w_t^{ni} &= \bar{w}_t^i \frac{h_t^{ni}}{\bar{h}_t^i}, \qquad (3) \\ \log w_t^{ni} &= \log \bar{w}_t^i + \log h_t^{ni} - \log \bar{h}_t^i, \\ &= \log \bar{w}_t^i + \left(X_t^{ni} - \bar{X}_t^i\right)\Phi^i + z_t^{ni}, \end{aligned}$$

where $\bar{X}_t^i$ is a vector of individual characteristics parameters' means, such as $Coll^n$, $SecEx_t^{ni}$ and $MktEx_t^{ni}$, $\bar{w}_t^i$ is the average wage in sector i and $\bar{h}_t^i$ is the average human capital in sector i.

In order to reduce the size of state space we discretize variables Age_t^n, $SecEx_t^{ni}$ and, $MktEx_t^n$ in such a way that they can only take the following values:

$$\begin{aligned} Age_t^n &\in \{26, 33, 40, 47, 54\}, \qquad (4) \\ SecEx_t^{ni} &\in \{4, 11, 18\}, \\ MktEx_t^n &\in \{4, 11, 18\}. \end{aligned}$$

Although estimation of the model without discretizing these variables could be possible, simulation is not feasible with endogenous wages. To accommodate for discretization, we assume that in each year a worker with age, A, moves to the next possible age, $A + k$, with a probability $1/k$, where $k = 7$ in this case[7]. When a worker reaches age 54 there is a $1/k$ probability that she will receive a lump-sum money and retire, to keep the population constant we assume that a new worker enters system for each retiree. When age increases market experience increases as well until 18 and does not increase further. Sectoral experience will evolve depending on workers decision to stay in their current sector, the maximum value for sectoral experience is also 18.[8] See Artuc (2006) for additional details.

If a worker changes sector, her sectoral experience is reduced to the minimum level. [9] If she stays in the same sector and her age increases at the same time, her sectoral experience increases to the next level:

$$\begin{aligned} \text{if } d_t^n &\neq d_{t-1}^n \implies SecEx_t^{ni} = 4 \\ \text{else if } d_t^n &= d_{t-1}^n \text{ and } Age_t^n = Age_{t-1}^n \implies SecEx_t^{ni} = SecEx_{t-1}^{ni}, \\ \text{else if } d_t^n &= d_{t-1}^n \text{ and } Age_t^n = Age_{t-1}^n + 7 \implies SecEx_t^{ni} = SecEx_{t-1}^{ni} + 7. \end{aligned} \tag{5}$$

In addition to the wage, each worker n, receives an idiosyncratic random utility, u_t^{ni}, from working in sector i. Where u_t^{ni} is distributed mean zero extreme-value with variance $\frac{\pi^2}{6}\nu^2$, see Patel, Kapadia and Owen (1976) for properties of the extreme-value distribution. Hence the instantaneous utility of being in sector i at time t is

$$U_t^{ni} = w_t^i \left(s_t^n, z_t^n, \xi_t\right) + u_t^{ni}, \tag{6}$$

where wage, $w_t^i \left(s_t^n, z_t^{ni}, \xi_t^i\right)$ is a function of the state variable s_t, random shock z_t^{ni} and aggregate state variable ξ_t^i as described above. The aggregate state variable ξ_t is a vector of relevant average wage and human capital levels in sectors such that $\xi_t = [\bar{w}_t^1..\bar{w}_t^I \ \bar{h}_t^1..\bar{h}_t^I \ ]'$. The non-random state vector s_t^n is consist of education, previous period's choice, sectoral

[7]Figure 16 shows how value functions of manufacturing workers would look like with k=1 (actual) and k=7 (approximation) using estimates from the next section.

[8]Estimating the life-time wage-tenure profile is out of the scope of this paper. We were not able to identify tenure-wage profile of workers above 40. We simply assume that for the last two age groups wage contribution of market and sectoral experience stay constant following the general shape of tenure-wage profile estimated in previous works, such as Mincer (1958).

[9]Unlike Keane and Wolpin (1997) we are keeping a one-dimentional sectoral experience variable in order to reduce the size of state-space.

and market experience:

$$s_t^n = \left[d_{t-1}^n \quad Coll^n \quad SecEx_t^{nd_{t-1}^n} \quad MktEx_t^n \right]'. \tag{7}$$

The non-random state vector s_t^n can also be considered as type of a worker. Workers who move from sector i to j will incur a moving cost, C^{nij}, if they change their sectors, so $C^{nij} > 0$ if $i \neq j$ and $C^{nij} = 0$ if $i = j$. If a worker changes her sector, the moving cost will be a function of her age, education and the sector she is moving in

$$C_t^{nij} = C_1^{Age_t^n} + C_2^j + Coll^n C_3,$$

this moving cost should not be taken literally as "financial cost", it will account for all unmodelled frictions and psychological costs as well.

For notational simplicity, consider a vector of all relevant state variables, η_t^n, for individual n, which are s_t^n, ξ_t, $z_t^n = [z_t^{n1}..z_t^{nI}]'$ and $u_t^n = [u_t^{n1}..u_t^{nI}]'$, such that $\eta_t^n = [s_t^n \ \xi_t \ z_t^n \ u_t^n]'$. The objective of an individual for any time $t = 1, ..., T$ is to maximize her present discounted total utility following a Bellman equation:

$$V_t\left(\eta_t^n\right) = \max_i \left(V_t^i\left(\eta_t^n\right)\right), \tag{8}$$

where sector (alternative) specific value functions are:

$$\begin{aligned} V_t^i\left(\eta_t^n\right) &= U_t^i\left(\eta_t^n\right) + E \max_j \beta \left\{ V_{t+1}^j\left(\eta_{t+1}^n\right) - C^{i,j}\left(s_{t+1}^n\right) \right\}, \\ &= U_t^i\left(\eta_t^n\right) + \beta \Omega_{t+1}^i\left(\eta_{t+1}^n\right) + \beta E V_{t+1}^i\left(\eta_{t+1}^n\right), \end{aligned} \tag{9}$$

for all periods where β is the discount factor. Thus, we can write the option value of moving as

$$\Omega_{t+1}^i\left(\eta_{t+1}^n\right) = E\left(\max_j \left\{ V_{t+1}^j\left(\eta_{t+1}^n\right) - V_{t+1}^i\left(\eta_{t+1}^n\right) - C^{i,j}\left(s_{t+1}^n\right) \right\} \right), \tag{10}$$

and note that $\Omega_{t+1}^i\left(\eta_t^n\right)$ can be calculated analytically upto a certain level. {See Appendix B for details. }

Timing:

At any given time period t the order of events for a worker is as follows: 1. Pays the moving cost $C > 0$ if her previous sector is different. 2. Works and enjoys her utility: $w_t^{ni} + u_t^{ni}$, 3. Learns the next period's random shocks $\left\{z_{t+1}^{nj}, u_{t+1}^{nj}\right\}_{j=1}^{6}$. 4. Chooses her sector. 5. Enters the next period $t+1$ and repeats steps 1-5 for $t+1$. Note that there is no aggregate uncertainty in the model except for the shock therapy (e.g. $\xi_t, \xi_{t+1}, \xi_{t+2}, ..., \xi_T, ...$ are known at time t).

Estimation of workers' problem:

Using the equations above we can calculate probability of a worker's transition from state s to s' {see Appendix B for details.} let us denote this probability with $m^{ss'}$, which is a function of s_t^n and expected next period alternative-specific values for each state.

In addition to the transition probabilities $m^{ss'}$, it is also possible to calculate probability of observing wage w_t^n given n's type s_t^n and average wage in her sector: $\bar{w}_t^i$. The estimation strategy is to maximize the log-likelihood function Λ:

$$\Lambda = \sum_{n=1}^{N} \sum_{t=1}^{T} \log \int_z \int_u m^{s_{t-1}^n s_t^n} \Pr\left(w_t^n\right) du_t^n dz_t^n.$$

Note that it is possible to solve the integral over u_t^n analytically in a way similar to multinomial logit models, however, the integral over z_t^n has to be calculated numerically with a quadrature or simulation based method. Thus, we use "method of simulated maximum likelihood" to estimate the parameters of interest. { See Appendix B for details. } Note that since some of the important distributional parameters, such as average sectoral experience of workers over 40, are not observed in the data. We calculate those parameters during the estimation process, then we repeat the estimation procedure recursively until the distribution of workers converge to a fixed point.

2.2 Aggregate Economy:

Let $l(s)$ be the ratio of workers with a given state $s \in \{1, ..., S\}$, where s is an index representing type of a worker, where total number of workers are normalized such that $1 = \sum_{s=1}^{S} l(s)$. There are 96 possible states thus S =96 types of workers (determined by all possible combinations of $Coll^n$, $SecEx_t^{ni}$, $MktEx_t^{ni}$ and d_t^n). For any given type s we can calculate time t labor allocation given time $t-1$ labor allocation and transition probabilities

$$l\left(s_t\right)=\sum_{s_{t-1}=1}^{S} m^{s_{t-1}s_t} l\left(s_{t-1}\right). \tag{11}$$

Let L_t be a vector representing the distribution of workers such as $L_t = [l\,(1)\ \ldots\ l\,(96)]'$. Consider a vector $\bar{V}_t(\xi_t)$ which is consist of $\bar{V}_t^i(s,\xi_t)$ for all possible states $s = 1, 2, ..., 96$ where $\bar{V}_t^i(s,\xi_t) = EV_t^i\left(\eta_t^n\right)$. Then L_t can be expressed as a function of previous period's distribution L_{t-1}, average wages and the vector of next period expected alternative specific values:

$$L_t = M\left(L_{t-1}, \xi_t, \bar{V}_t(\xi_t)\right), \tag{12}$$

where ξ_t is a vector of average wage and human capital levels. Average wages are endogenous from the aggregate perspective. Let production functions be

$$y_t^i = B^i\left(L_t^i\bar{h}_t^i\right)^{b_L^i}\left(K^i\right)^{b_K^i}\prod_{j=1}^{I}\left(q_t^{ji}\right)^{b_j^i}, \tag{13}$$

where L_t^i is the ratio of workers in sector i, where $L_t^i = \sum_{s\in S_i} l\,(s)$ and S_i is the set of types of worker where $d_t^n = i$ (types that are from sector i), $\bar{h}_t^i$ is average human capital, K^i is capital, and q_t^{ji} is amount of product from sector j used in production in sector i. We assume that capital is specific to sectors similar to Ricardo-Viner models as in ACM. (We also experimented with perfect capital mobility simulations and found that qualitative implications of the model, in general, are unchanged).

Each worker will receive her real marginal product, given price level p_t^i and consumer price index φ_t:

$$w_t^{ni} = \frac{p_t^i}{\varphi_t}\frac{\partial y_t^i}{\partial L_t^i}\frac{h_t^{ni}}{\bar{h}_t^i}, \tag{14}$$

thus

$$\bar{w}_t^i = \frac{p_t^i}{\varphi_t}\frac{\partial y_t^i}{\partial L_t^i}. \tag{15}$$

Therefore the average wages can be written as a function of L_t^i and $\bar{h}_t^i$ (hence the distribution of workers L_t),

$$w_t^i = b_L^i \left(L_t^i \bar{h}_t^i\right)^{b_L^i - 1} \bar{h}_t^i \zeta_t^i \frac{p_t^i}{\varphi_t}, \tag{16}$$

where ζ_t^i is a part of the Cobb-Douglas production function, $\zeta_t^i = B^i \left(K^i\right)^{b_K^i} \prod_{j=1}^I \left(q_t^{ji}\right)^{b_j^i}$. Finally consumption preferences are described by a simple utility function:

$$\Upsilon_t = \prod_{j=1}^{I} \left(q_t^{jc}\right)^{\theta_j}, \tag{17}$$

where q_t^{jc} is quantity of j consumed at time t and θ^j's are the weights. In the next section we discuss estimation results of workers' problem and calibration of production functions.

3 Estimation and Calibration of Parameters:

We are interested in estimation to find plausible parameters for the simulations, thus in cotrast to papers from labor economics literature, our main focus will be counterfactual trade liberalization simulations. We estimate human capital accumulation and mobility parameters jointly, from each worker's simulated likelihood contribution. Then we calibrate production function parameters from Breau of Economic Analysis data, assuming Cobb-Douglas forms.

Data

For estimation of the workers' problem, we use 1979 cohort of the National Longitudinal Survey of Youth (henceforth NLSY) as our main data set. NLSY is widely used in estimation of occupational choice models, since it follows individuals over years and provides detailed information on work history. The sectoral experience variable, $SecEx_t^{ni}$, can be easily constructed from NLSY. One important restriction of NSLY is it follows individuals annually until about age 40, so we can not identify parameters for older individuals in the model. In order to identify moving cost parameter C^{nij} for individuals over 40 we include Current Population Survey March sample (henceforth CPS) in our estimation. Since sectoral experience is not observed in CPS, we can not use it to calculate likelihood contribution of observed wages. The average wages are also calculated using CPS because NLSY sample size is much smaller.

Initially, NLSY has 12,686 people in the sample, consisting of 6,403 males and 6,283 females. Like most of the other mobility models, we only pick males for our sample (such as Keane and Wolpin (1997) and ACM). Moreover, we take blacks and Hispanics out of our sample, who are over-sampled by the NLSY, again following the previous research. This reduces our sample size by approximately 40%, so we are left with 3,790 individuals. The individuals in our sample are between ages of 14 and 21 as of year 1979. We use observations, from years 1983 to 1994, of individuals who were at least 23 years old, worked at least 26 weeks in the observed year and who do not have any missing industry information from previous years. For example if a certain individual's data is missing for 1990, we do not use him after 1990 since we can not construct sectoral experience data for him after the missing observation. If a certain individual is observed less than 7 years between 1983 and 1994, we take him out from the sample. We do not use observations of individuals whose implied full time real annual wage income is less than $5000, or more than $300,000 (where the base year is 2000). We end up with 1190 individuals in the sample. [10]

Neal (1999) reports that there are coding errors in NLSY79 regarding occupations. A similar error is also present for industry codings. In order to minimize this problem, we use the following method as in Neal (1999); whenever a sector change is reported, we require that the worker has to change his employer as well, otherwise it is considered as a coding error and the original sector is kept. Tenure of workers with their current employer is reported in NLSY.

The CPS sample is from 1983 to 2001 and constructed in a similar way: We use white and male individuals, who are between 23 and 57, and who worked at least 26 weeks in a given year. We have a minimum of 11,857 and a maximum of 20,211 people in our final sample between the years 1984 and 2001 (sample size changes every year). In CPS, reported mobility rates are 5 months' mobility rather than annual mobility, we follow a procedure similar to ACM to correct transition probabilities.

Table 1 summarizes distribution of workers across sectors, age, sectoral experience and education groups in both NLSY and CPS samples. Note that sectoral experience is not available for CPS sample and NLSY sample includes people only up to age 40. Manufacturing and agriculture workers (henceforth manuf.) are approximately 27%, metal workers are about 4%, service workers except trade workers (henceforth service) are about 49% and finally

[10]Keane and Wolpin (1997) end up with 1373 individuals in their final sample following a similar method.

Table 1: Distribution of Workers.

Panel A: Sectors

Sector	*NLSY*	*CPS*
Manuf	27.7%	27.2%
Metal	3.8%	3.3%
Service	49.5%	52.9%
Trade	19.0%	16.7%

Panel B: Age

Age	*NLSY*	*CPS*
23 to 29	58.8%	18.6%
30 to 36	41.2%	25.4%
37 to 43	NA	23.4%
44 to 50	NA	18.5%
51 to 57	NA	14.3%

Panel C: Sectoral Experience

Experience	*NLSY*	*CPS*
1 to 7	86.0%	NA
8 to 14	14.0%	NA
14 to 18	NA	NA

Panel D: Education

Education	*NLSY*	*CPS*
No-college	60.3%	59.1%
College	39.7%	40.9%

wholesale and retail trade workers (henceforth trade) are close to 20% of the total sample (see Panel A). Unlike ACM, our analysis does not rely on calculation of aggregate transition probabilities, which allows us to have a very small sector, such as metal. Calculation of aggregate transition probabilities requires observing some workers from each sector moving to every possible direction, which is impossible when one of the sectors is small or when there are many worker types. Panel B shows age distribution and Panel C shows sectoral experience distribution in the sample. As illustrated in Panel D, about 40% of workers have at least one year of college education in the sample.

Table 2: Transition Probabilities (CPS).

Panel A: No College Education

Age	*Manuf*	*Metal*	*Service*	*Trade*
23 to 29	0.067	0.076	0.055	0.090
30 to 36	0.041	0.050	0.032	0.061
37 to 43	0.030	0.035	0.021	0.041
44 to 50	0.022	0.035	0.017	0.036
51 to 57	0.018	0.016	0.014	0.026

Panel B: Some College Education

Age	*Manuf*	*Metal*	*Service*	*Trade*
23 to 29	0.065	0.085	0.039	0.104
30 to 36	0.041	0.065	0.019	0.060
37 to 43	0.032	0.048	0.015	0.046
44 to 50	0.033	0.046	0.011	0.042
51 to 57	0.025	0.050	0.010	0.033

Panel C: Transition Marix

	Manuf	*Metal*	*Service*	*Trade*
Manuf	0.963	0.002	0.025	0.011
Metal	0.019	0.954	0.020	0.007
Service	0.011	0.001	0.977	0.011
Trade	0.017	0.002	0.039	0.943

Table 2 shows example transition probabilities from different age groups, education groups and sectors. Panel A presents probabilities of sector change for workers with no college education while Panel B shows for those with at least one year of college education. The effect of education on probability of sector change is ambiguous. However, it is clear that probability of sector change is decreasing with age for both education groups. Panel C shows transition probability from one sector to another. As one would expect, probability of moving out of a larger sector is lower than probability of moving out of a smaller sector, and probability of moving into a larger sector is higher than probability of moving into a smaller sector.

Estimation Results

Wages are deflated by the CPI, and normalized so that over the whole sample the average annualized wage is equal to unity as in ACM. We find that the variance of preference shocks is extremely large: The parameter of the extreme value distribution ν is about 1.5 (reported in Table 3 - Panel A) which means that standard error of the idiosyncratic utility shock is approximately equal to 1.9. In the Table 4 - Panel A the standard error of wage shock. σ_z is reported as 0.41. The estimation results show that idiosyncratic shocks and unmodelled frictions play a very important role in decision of workers.

The estimated moving cost, reported in Table 3 - Panel B, starts from 4.5, increases with age, and end up being as large as 5.9 for the oldest type. These numbers are large but not surprising since similar projects with idiosyncratic utility shocks such as Sullivan (2006), Kennan and Walker (2003), and ACM also report such large mobility costs. For example ACM find a moving cost equal to 6.5 times of average annual wage. We will present estimation results of an extended model with unobserved heterogeneity to shed some light on possible reasons of this unrealistically large moving costs in a later section. Panel C shows the sector specific component of the moving cost, which is how much more (or less) the moving cost would be depending on the sector a person chooses to work in. The moving costs reported in Panel B can be 3.2 more if a worker is moving to metal sector (which is the smallest sector) or 1.5 less if a person is moving to service sector (the largest sector). Panel D shows that people with some college education bear larger moving costs, this can be attributed to the fact that people with more education earn higher wages. Because of higher wages, their wage offers fluctuate more in levels (obviously not necessarily in logs), hence for a similar mobility rate, as reported in Table 2, people with more education should face larger moving costs.

Table 3: Estimation - Moving Cost.

Panel A: Idiosyncratic Shock Parameter

		Coefficient	*t-stat*
	ν	1.50	13.06

Panel B: Age specific cost

Parameter	*Age*	*Coefficient*	*t-stat*
C_1^1	***Age 26***	4.55	13.59
C_1^2	***Age 33***	5.02	12.86
C_1^3	***Age 40***	5.07	10.08
C_1^4	***Age 47***	5.32	9.73
C_1^5	***Age 54***	6.08	9.59

Panel C: Additional sector specific cost

Parameter	*Sector*	*Coefficient*	*t-stat*
C_2^1	***Manuf***	0.00	N/A
C_2^2	***Metal***	3.24	11.15
C_2^3	***Service***	-1.73	-12.00
C_2^4	***Trade***	-0.72	-7.93

Panel D: Additional education specific cost

Parameter	*Education*	*Coefficient*	*t-stat*
C_4	***College***	2.90	2.90

Table 4: Estimation - Human Capital.

Panel A: Std. Dev. Of Wage Shock

		Coefficient	*t-stat*
	σ_z	0.413	317.97

Panel B: Education Parameters

Parameter	*Sectors*	*Coefficient*	*t-stat*
ϕ_1^1	***Manuf***	0.131	8.96
ϕ_1^2	***Metal***	0.060	2.37
ϕ_1^3	***Service***	0.200	13.73
ϕ_1^4	***Trade***	0.160	11.35

Panel C: Sectoral Experience Parameters

Parameter	*Sectors*	*Coefficient*	*t-stat*
ϕ_2^1	***Manuf***	0.025	14.28
ϕ_2^2	***Metal***	0.012	2.66
ϕ_2^3	***Service***	0.032	22.70
ϕ_2^4	***Trade***	0.037	18.21
	Education	*Coefficient*	*t-stat*
ϕ_4	***College***	-0.008	-4.83

Panel D: Market Experience Parameters

Parameter	*Sectors*	Coefficient	*t-stat*
ϕ_3^1	***Manuf***	0.007	4.32
ϕ_3^2	***Metal***	0.011	3.36
ϕ_3^3	***Service***	0.004	2.77
ϕ_3^4	***Trade***	0.000	0.18
	Education	Coefficient	*t-stat*
ϕ_5	***College***	0.011	5.61

Table 4 reports estimates of the wage equation related parameters. Panel B shows that return on education is the highest for service sector and the lowest for metal sector. This is an expected result since sectors like professional, finance, public are parts of service sector. Return on sectoral experience for different sectors and education levels is shown in Panel C. Return on sectoral experience varies between 0.012 to 0.025. This high return on sectoral experience contributes to the high moving cost of older workers. [11] Finally, Panel D reports the return on market experience (which is equivalent to age in our model, since we do not model labor force participation as an alternative choice).

Calibration

The parameters b_L^i, b_K^i, b_j^i and ζ_A^i are calibrated from the Bureau of Economic Analysis data, they are reported in Panel A and Panel B of Table 5 . We simply assume that cost shares of labor and inputs are parameters of the Cobb-Douglas production functions. We pick ζ_A^i's such that observed average wages are as close as possible to the implied wages, given the distribution of labor. The parameters of Cobb-Douglas utility function, θ_i's are calibrated from Consumer Price Index data, which are reported in Panel C of Table 5 . ACM and Artuc (2006) also follow a similar calibration method and provide more detail. For the estimation and the simulations, we assume that discount factor β is equal to 0.96. We were not able to estimate β since it is poorly identified by our model.

4 Simulation:

4.1 Autarky Steady State:

As first step for the counterfactual exercise, we simulate autarky steady state to calculate the initial labor distribution, L_t, which will gradually converge to the free trade distribution after the trade shock. Here we use the subscript A instead of t to refer to any time period before the shock. Although we call it autarky for notational simplicity, we assume that there

[11] The return on sectoral experience we find here can potentially be upward-biased, as we do not model occupational choice. A very recent paper by Kambourov and Manovskii (2009) showed that at one-digit level, return on sectoral experience is about half of return on occupational experience. In our data about 52% of workers who change sectors change occupations as well, while 49% of workers who change occupations change sectors as well. To capture effects of occupational and sectoral mobility more accurately, we need to add occupational mobility to our model, which is left for future research. Sensitivity analysis of simulations with alternative sectoral experience values are available upon request.

Table 5: Calibration - Production and Utility Functions.

Panel A: Production Function Input Shares

	Manuf	*Metal*	*Service*	*Trade*
Labor	0.18	0.25	0.37	0.37
Capital	0.13	0.13	0.29	0.27
Manuf	0.35	0.07	0.08	0.04
Metal	0.05	0.29	0.01	0
Service	0.24	0.19	0.23	0.3
Trade	0.05	0.07	0.02	0.02

Panel B: Production Function Constant

	Manuf	*Metal*	*Service*	*Trade*
$log\zeta_A^i$	10.8404	9.0984	10.6266	9.75

Panel C: Utility Function Shares

	Manuf	*Metal*	*Service*	*Trade*
θ_i	0.4	0	0.6	0

is actually trade in the manufacturing sector before the liberalization in the metal sector. We use equations from previous sections to illustrate autarky steady state:

$$\begin{aligned}
\bar{w}_A^i &= b_L^i \left(L_A^i \bar{h}_A^i\right)^{b_L^i - 1} \bar{h}_A^i \zeta_A^i \frac{p_A^i}{\varphi_A}, \\
L_A &= M\left(L_A, \xi_A, \bar{V}_A(\xi_A)\right), \\
\bar{V}_A^i(s, \xi_A) &= \tilde{w}_A^i(s, \xi_A) + \beta\Omega_A^i(s', \xi_A) + \beta E_s \bar{V}_A^i(s', \xi_A), \\
\bar{h}_A^i &= \exp\left(\bar{X}_A^i \Phi^i\right),
\end{aligned} \tag{18}$$

where $\tilde{w}_A^i$ is the expected autarky wage for type s workers in sector i, and $\xi_A = [\bar{w}_A^1..\bar{w}_A^I\ \bar{h}_A^1..\bar{h}_A^I]'$ is the vector of autarky average wage and human capital levels, $\bar{X}_A^i$ is the average of human capital parameters used in wage equation (3). For simplicity we assume that $p_A^i = 1$ and $\varphi_A = 1$. Note that λ_A^i and $\bar{h}_A^i$ can be calculated from L_A, since they are ratio of workers and average human capital in sector i respectively, where L_A is distribution of types in the economy. Other relevant variables are output:

$$y_A^i = \left(L_A^i \bar{h}_A^i\right)^{b_L^i} \zeta_A^i,$$

and income spent on i:

$$\mu_A^i = \sum_{j=1}^{I} \left[b_i^j + \theta_i \left(b_L^j + b_K^j\right)\right] y_A^j p_A^j.$$

Define $X_A = [w_A^1 \;..\; w_A^I \; \bar{V}_A \; L_A]'$, the simulation exercise can be defined as a problem of finding a fixed point $X_A = F(X_A)$ where $F(.)$ is a function described by the set of equations (18). The fixed point is calculated numerically, similar to Artuc, Chaudhuri and McLaren (2008).

4.2 Transition:

We assume that with the abolishment of tariffs in the metal sector, the prices will decrease about 30%, thus $p^{Metal} = 0.7$ when $t > 0$. First, we have conditions for the transition, similar to the autarky steady state condition (18) :

$$\begin{aligned} \bar{w}_t^i &= b_L^i \left(L_t^i \bar{h}_t^i\right)^{b_L^i - 1} \bar{h}_t^i \zeta_t^i \frac{p_t^i}{\varphi_t}, \qquad (19) \\ L_t &= M\left(L_{t-1}, \xi_t, \bar{V}_t(\xi_t)\right), \\ \bar{V}_t^i\left(s_t, \xi_t^n\right) &= \tilde{w}_t^i\left(s_t, \xi_t\right) + \beta \Omega_{t+1}^i\left(s_{t+1}, \xi_{t+1}\right) + \beta E_s \bar{V}_{t+1}^i\left(s_{t+1}, \xi_{t+1}\right), \\ \bar{h}_t^i &= \exp\left(\bar{X}_t^i \Phi^i\right). \end{aligned}$$

However this time we can no longer assume that $p_t^i = 1$ or $\varphi_A = 1$, since prices change during transition. In addition to prices the inputs used in production will also change, thus the parameter ζ_t^i will be different from the calibrated parameter ζ_A^i. We normalize these parameters with their autarky values, such that $\tilde{x}_t$ denotes x_t/x_A. The change in consumer price index can be calculated with the change in prices

$$\tilde{\varphi}_t = \prod_{i=1}^{I} \left(\tilde{p}_t^i\right)^{\theta_i} \qquad (20)$$

The change in prices (for service and trade) can be calculated with the change in income spent on each product and quantities produced, simply by exploiting the Cobb-Douglas form of demand and production functions

$$\mu_t^i = \sum_{j=1}^{I} \left[b_i^j + \theta_i \left(b_L^j + b_K^j\right)\right] y_t^j p_t^j, \tag{21}$$
$$\tilde{p}_t^i = \frac{\tilde{\mu}_t^i}{\tilde{y}_t^i}.$$

The change in ζ_t^i can be calculated using the change in prices and output

$$\tilde{q}_t^{ij} = \frac{\tilde{p}_t^i}{\tilde{p}_t^j} \tilde{y}_t^i, \tag{22}$$
$$\tilde{\zeta}_t^i = \prod_{j=1}^{I} \left(\tilde{q}_t^{ij}\right)^{b_j^i}.$$

Finally, the change in output can be written as a function of change in total human capital in sectors and the change in ζ_t^i

$$\tilde{y}_t^i = \left(\frac{L_t^i \bar{h}_t^i}{L_A^i \bar{h}_A^i}\right)^{b_L^i} \tilde{\zeta}_t^i. \tag{23}$$

Define vector $X_t = [w_t^1 \ .. \ w_t^I \ \bar{V}_t \ \tilde{y}_t^1 \ .. \ \tilde{y}_t^I \ \tilde{p}_t^1 \ .. \ \tilde{p}_t^I]'$, and matrix $X = [X_1 \ X_2 \ .. \ X_T]$. We assume that for $t > T$, $X_t = X_{t-1}$. Let $X = G(X, L_A)$ be a function defined by equations (19), (20), (21), (23) and (22). Finding the transition values is also equivalent to finding a fixed point given the autarky labor allocation, L_A. Similar to the autarky problem, this problem can also be solved numerically. We check if X_T is indeed the free trade steady state, if not we increase T and find another fixed point. See Artuc, Chaudhuri and McLaren (2008) or Artuc (2006) for details.

4.3 Results

We first simulate the model for the autarky steady state, where all prices are normalized to unity. Table 6 shows distributions, average log-wages and average education levels of all workers along with average sectoral experience of young workers across sectors, both for simulated autarky steady state and actual data. The calibrated production functions combined with the structural estimates produce fairly close distributions to the actual data although they were calibrated and estimated seperately.

After calculating the steady state, we assume that a shock-therapy trade liberalization in the metal sector decreases its product's price by 30%, forcing it to be equal to the world price at $t = 1$. [12] We assume that service and trade sector outputs are non-tradable, while manufacturing sector output is tradable, which makes manufacturing price constant over time. Given the initial autarky labor allocation, outputs and prices, we calculate transition of labor allocation, wages, values of workers, prices, output and demand of goods after the trade shock.

Table 6: Distribution of Workers from Simulations and Data

		Manuf	**Metal**	**Service**	**Trade**
Labor	*Data*	0.27	0.03	0.53	0.17
	Simulation	0.28	0.04	0.51	0.16
Log-wage	*Data*	10.21	10.19	10.23	10.05
	Simulation	10.23	10.21	10.25	10.06
College	*Data*	0.31	0.34	0.44	0.32
	Simulation	0.3	0.2	0.44	0.31
Sectoral Exp.	*Data*	5.65	5.17	5.16	4.87
	Simulation	6.32	6.88	5.8	5.59

Figures 1-3 show gross flows of workers, that is percentage of workers leaving their sectors. Figure 1 is for workers with average 4 years of sectoral experience and who are about 26 years old. Initially, approximately 19% of "trade" workers leave their sector, and 14% of other workers leave their sector every year. After the trade shock, this percentage increases to 29% for "metal" workers, decreases to 13% for "manuf" workers and stays approximately the same for "trade" and "service" workers. Figure 2 presents gross flows of workers with average 4 years of sectoral experience and who are about 54 years old; while Figure 3 shows gross flows of 54 years old workers with at least 18 years of sectoral experience. The general trend of gross flows are the same in all three figures: Sectoral mobility decreases with age and experience.

[12] This is basically a small open economy assumption. Since the US uses about 10% of word metal output, a metal sector liberalization will not affect world price significantly. We experimented with an alternative specification where world price is determined endogenously and found that the qualitative implications are unchanged. Results available upon request.

Figure 4 shows the adjustment of wages after the trade shock: We find that gross flow of workers are negatively correlated with wages. The adjustment process of “metal” sector is very simple but interesting: Initially price of “metal” sector product decreases, causing the wages in ”metal” sector to decrease. Workers start leaving “metal” sector, causing large out-flows, which eventually increases wages in “metal” sector. The long run free trade wage in “metal” sector is, however, lower than the autarky wage. For the other sectors, the adjustment process is quite subtle: First, it should be noted that “metal” sector product is not consumed, but used mostly as an input in “manuf” and “metal” sectors. Therefore, ”metal” price has no direct effect on CPI or real wages. However, the decrease in “metal” price increases its use as an input, and increases the marginal product of “manuf” workers, causing an increase in wages. Other sectors’ wages are do not change much after the shock. Figure 5 displays change in output, showing a notable increase in the “manuf” output and a very large decrease in “metal” output. Like wages, the other sectors’ outputs are not significantly affected from the trade shock.

Figure 6 shows the change in demand (from both consumers and producers) for each product. As expected, demand for “metal” increases significantly with the price cut. Demand for “manuf” also increases, even though there is no change in its price, because of the general increase in output after the shock. (Since there are no market failures or externalities in our model, it is safe to assume that GDP increases after the trade liberalization although we do not explicitly calculate it). The demand for “service” also increases, but the change is much smaller compared to “manuf” because ”service” price increases with demand. Note that “manuf” price is constant as it takes the world price. Figure 7 shows change in prices. Going back to Figure 4, the changes in “service” and “trade” prices pull the ”service” and “trade” wages up, while workers moving into “service” and “trade” from “metal” sector push wages down. These two opposite forces cause wages in “service” and ”trade” change only slightly: a small increase for “service” and a small decrease for “trade”.

Figures 8-11 show how low-skill workers’ value change right after the trade shock.[13] (The results for high-skill workers are very similar and shown in Figures 12-15). Since “metal” sector output is used intensively only in “manuf” and “metal” and not consumed, “service”

[13] Although we originally have only 96 types of workers, as shown in (4), we can calculate values for more a finely partitioned state space, e.g. Age $\in \{23, 24, 25, 26, 27, ..., 57\}$, using the aggregate distribution of workers and wages from the simulations.

and “trade” sector workers are less affected from the trade shock compared to others. Note that size of “metal” sector is fairly small and flows out of metal sector do not significantly change labor allocations in other sectors. (We can safely ignore tariff revenues from “metal” sector because of its small size).

Figure 8 shows that “manuf” workers, in general, benefit from the shock, consistent with the fact that output increases more compared to the increase in number of workers in “manuf”. The gains increase with age and experience, reaching maximum level for middle aged people who have worked in the “manuf” sector for their entire life. The gains decrease with age after a certain age because expected time horizon to enjoy benefits of free trade decreases. When a worker is sufficiently close to retirement, she would only care about purchasing power of her retirement savings. We assume that when a worker retires, she receives a lump-sum money which is not a function of price levels, thus retired workers are worse off after the shock since prices of ”services” increase after the shock. An equally plausible assumption would be assuming an inflation-protected retirement benefits scheme, then retired workers would be unaffected from the shock. Since the difference is trivial we do no show simulation results for the alternative approach. However, we believe that to shed more light on this issue, a more detailed retirement model is required, which is out of the scope of this paper.

Younger workers benefit less compared to middle aged, because option value of younger people decrease after the trade shock - which is a significant portion of their value as shown in (10). As a worker’s moving cost increases, her option value decreases, so it becomes fairly small when a worker gets old. After the shock, “metal” sector becomes an unattractive alternative for working in “manuf”, causing a notable drop in young “manuf” workers’ option value. It is very unlikely for a person, who has been working in “manuf” for many years to move to other sectors, so developments in other sectors do not change older workers’ option value much.

Figure 9 shows change in “metal” workers’ value, which is almost the opposite of previous figure. Young workers are hurt less because of the increase in their option value, while older workers are hurt more. Older and middle aged workers’ inability to move to other sector makes them lose more compared to young. The story for the workers, who are close to their retirement, is exactly the same as “manuf” sector.

Figure 10 displays change in values of “service” and Figure 11 shows changes in values of “trade” workers. These two sectors are only slightly affected from the trade shock as they are not using “metal” in their production. “Service” workers are slightly better off, while “trade” workers are slightly worse off. The general shape of the value functions surface is similar to other sectors: Middle aged workers benefit more if they workers benefit in general, and hurt more if workers are hurt in general (compared to young). We would like to call it a “mirror effect”. Trade shocks affect older people by a large scale both positively and negatively, while younger people are affected usually in the same direction as older people in their sector but by a much smaller scale. (Yet, it is theoretically possible that old people are worse off in import competing sector while young people are better off.)

Our results show that there is a relation between age and supporting free trade, but the simulated trade liberalization in the metal manufacturing does not imply that old workers would be less supportive of free trade compared to young, as it is seen in the Pew Survey.[14] The counterfactual exercise presented here is of a very small sector, so the distributional effects of a long term globalization can not be studied from our graphs. Analyzing long term globalization in detail and explaining results of the Pew Survey is out of the scope of this paper. But just to shed some light on this interesting issue, we simulated an hypothetical trade liberalization in “manuf” sector. We find that all workers except middle aged and older “manuf” workers benefit from trade liberalization, including young “manuf” workers. So a liberalization in ”manuf” sector could be more consistent with the Pew Survey. We also experimented with perfect capital mobility and found that qualitative implications of our base simulations are unchanged. (Results are available upon request).

5 Unobserved Heterogeneity: An Extended Model

As we discussed earlier, the moving cost we estimate should not be taken as a financial cost since there are many unmodelled frictions in the labor market which is captured by the moving cost. In an alternative setup, we assume that there is unobserved heterogeneity, particularly two types of workers: type I - workers who can move after paying some moving cost, and type II - workers who can not move at all. Having these two unobserved types will allow us to capture some of the unmodelled frictions which would otherwise be captured by

[14] We provide a simple analysis of the Pew Global Attitudes Survey in Appendix C for descriptive purposes.

the moving cost. In the original model we had 96 types, with inclusion of a binary unobserved heterogeneity we end up with 192 types. We assume that unconditional probability of being type II is α, probability of transition from type I to type II is γ_1 and probability of transition from type II to type I is γ_2.

Consider this special case: If one's type in the next period is independent of her current type then, $\gamma_1 = \alpha$ and $\gamma_2 = 1 - \alpha$. For this special case, we can think of type I workers as those who can get job offers this year, and type II workers as those who can not get job offers. Then any friction captured by inclusion of unobserved types for this special case can be considered as search frictions. Another underlying friction can be time persistence of utility or wage shocks. If a worker likes one sector better than others, because of financial or non-financial reasons, her preference this year is most likely correlated with her preference last year. For example, the worker might be a very talented sales-person resulting in higher wages for her in trade sector, or her spouse might also be a sales-person and she might want to work in the same company with him. Both of these shocks are time persistent, inconsistent with our *iid* assumptions. By introducing two unobserved types, we allow a simple persistence in the idiosyncratic moving cost.

Probability of being type II unconditional on history depends on observed state of an individual. Assume that probability of being type II given the observed characteristics is $\alpha(s_t)$, where s_t is the observed characteristics (or state) of the individual. This probability can easily be calculated from the aggregate distribution vector, L_t. Also assume that probability that a worker will stay in her sector is $\psi(s_t)$.

If a worker has moved in last period, we are sure that she was type I in last period, so for her to be type I again this period is

$$\Pr(I|s_t, s_{t-1}) = 1 - \gamma_1.$$

Similarly if a worker has moved two periods before today, she was a type I then so her probability of being type I today is

$$\Pr(I|s_t, s_{t-1}, s_{t-2}) = \frac{p^{11}}{p^{11} + p^{12}},$$

where

$$
\begin{aligned}
p^{11} &= \gamma_1\gamma_2 + (1-\gamma_1)^2\,\psi(s_{t-1}),\\
p^{21} &= (1-\gamma_2)\,\gamma_2 + \gamma_2\,(1-\gamma_1)\,\psi(s_{t-1}),\\
p^{12} &= \gamma_1\,(1-\gamma_2) + (1-\gamma_1)\,\gamma_1\psi(s_{t-1}),\\
p^{22} &= (1-\gamma_2)^2 + \gamma_2\gamma_1\psi(s_{t-1}).
\end{aligned}
$$

If a worker has not moved in the last two periods, the probability that she is a type I is

$$
\Pr(I|s_t, s_{t-1}, s_{t-2}) = \frac{\{1-\alpha(s_{t-2})\}\,\psi(s_{t-2})\,p^{11} + \alpha(s_{t-2})\,p^{21}}{\{1-\alpha(s_{t-2})\}\,\psi(s_{t-2})\,\{p^{11}+p^{12}\} + \alpha(s_{t-2})\,\{p^{21}+p^{22}\}}.
$$

Finally, if a worker's history is unknown then her probability of being type I is

$$
\Pr(I|s_t) = 1-\alpha(s_t).
$$

We use these probabilities in maximum likelihood contributions of individuals. Ideally, we could go back more in history of workers, but we prefer to go back only two periods since it is sufficient to identify the parameters we are interested in. Going back more in history would require computing all possible paths, which is computationally (and analytically) infeasible.

Table 7 shows that estimated moving costs decrease substantially with inclusion of unobserved heterogeneity. We now find that moving cost parameter C_1^1 is equal to 1.77 and C_1^5 is equal to 3.22, while the same parameters are equal to 4.55 and 6.1 respectively without unobserved heterogeneity. Other results presented in Tables 7 and 8 are very similar to 3 and 4. Thus parameter estimates, excluding mobility costs, are not affected much from the introduction of unobserved heterogeneity. Another interesting parameter is α, which is estimated as high as 0.70. This can be interpreted as, 70 percent of workers can not move either because of search frictions or time persistence of shocks. Finally, we find that $\lambda_1 = 0.37$, thus it can be inferred that unobserved types show some persistence, since it is much smaller than 0.70. When we repeat the simulation exercise for the extended model, we find that inclusion of unobserved heterogeneity does not change the qualitative implications of the main model (figures available upon request). We also experimented with unobserved heterogeneity in wage offers (by allowing unobserved sector specific human capital), however we were not

Table 7: Estimation - Moving Cost (Unobserved Heterogeneity).

Panel A: Idiosyncratic Shock Parameter

	Coefficient	*t-stat*
ν	1.19	8.95

Panel B: Age specific cost

Parameter	*Age*	*Coefficient*	*t-stat*
C_1^1	***Age 26***	1.77	3.71
C_1^2	***Age 33***	2.33	4.61
C_1^3	***Age 40***	2.34	4.01
C_1^4	***Age 47***	2.59	4.21
C_1^5	***Age 54***	3.22	4.88

Panel C: Additional sector specific cost

Parameter	*Sector*	*Coefficient*	*t-stat*
C_2^1	***Manuf***	0.00	N/A
C_2^2	***Metal***	2.59	8.18
C_2^3	***Service***	-1.51	-9.32
C_2^4	***Trade***	-0.61	-7.94

Panel D: Additional education specific cost

Parameter	*Education*	*Coefficient*	*t-stat*
C_4	***College***	0.30	3.31

Panel E: Types

Parameter	*Probability*	*Coefficient*	*t-stat*
α	Pr(II)	0.70	18.25
λ^1	Pr(I to II)	0.37	6.12
λ^2	Pr(II to I)	0.15	N/A

able to identify distributional parameters for this specification. See Appendix A, "Unobserved Heterogeneity 2" section for this specification and related tables. One robust finding we get is: With introduction of unobserved heterogeneity (whether it is in utility shocks or human capital), estimated moving costs become smaller as unobserved heterogeneity provides addition frictions to labor mobility.

Finally, in Table 9 we compare estimated moving costs and welfare effects of trade liberalization under different unobserved heterogeneity assumptions. Welfare effects are quantitatively close for all simulations (except for type II workers who can not move), and the qualitative results (i.e. order of magnitude) are robust for all types. Type II workers benefit more (or hurt more) after a trade liberalization depending on their sector. This is because type II workers have much smaller option values as they are stuck to their sectors in the short-run.

6 Conclusion

We introduced a model which can be used to analyze distributional effects of trade liberalization. Our initial setting was somehow similar to ACM, but we followed a completely different econometric strategy which allowed us to introduce richer ex-ante and endogenous worker heterogeneity. Although this strategy prevented us from using their compact Euler-equation conditions, we simplified the estimation process by discretizing state-space. Using NLSY and CPS, we estimated mobility parameters and human capital accumulation process jointly. With estimates of these structural parameters and calibrated production functions, we simulated a counterfactual trade shock in metal manufacturing sector (which was subject to shocks recently, steel sector in particular.) We find that:

(1) Estimated moving costs are large and increase further with age. Preference shocks are important in explaining labor mobility, therefore psychological and unobserved factors play a crucial role in mobility decisions.

(2) High moving costs found in this paper (and in ACM) might be partially due to omission of unobserved heterogeneity, which may be caused by search frictions and persistence of shocks.

(3) After a trade shock in the metal sector, mainly "metal" and "manufacturing" work-

Table 8: Estimation - Human Capital (Unobserved Heterogeneity).

Panel A: Std. Dev. Of Wage Shock

	Coefficient	*t-stat*
σ_z	0.412	317.97

Panel B: Education Parameters

Parameter	*Sectors*	*Coefficient*	*t-stat*
ϕ_1^1	***Manuf***	0.131	8.86
ϕ_1^2	***Metal***	0.062	2.41
ϕ_1^3	***Service***	0.202	13.89
ϕ_1^4	***Trade***	0.159	11.11

Panel C: Sectoral Experience Parameters

Parameter	*Sectors*	*Coefficient*	*t-stat*
ϕ_2^1	***Manuf***	0.025	14.12
ϕ_2^2	***Metal***	0.013	2.91
ϕ_2^3	***Service***	0.032	22.67
ϕ_2^4	***Trade***	0.031	14.95
	Education	*Coefficient*	*t-stat*
ϕ_4	***College***	-0.011	-6.30

Panel D: Market Experience Parameters

Parameter	*Sectors*	Coefficient	*t-stat*
ϕ_3^1	***Manuf***	0.007	4.34
ϕ_3^2	***Metal***	0.009	2.77
ϕ_3^3	***Service***	0.004	2.68
ϕ_3^4	***Trade***	0.004	2.67
	Education	Coefficient	*t-stat*
ϕ_5	***College***	0.013	6.17

Table 9: Comparison of Simulated Welfare Effects

Panel A: Idiosyncratic Moving Costs

		Bechmark	Unobserved Hetero.		Unobserved Hetero. 2	
Age	***Sec. Exp***	***All***	***type I***	***type II***	***type A***	***type B***
26	*4*	4.55	1.77	NA	3.14	3.14
40	*4*	5.07	2.34	NA	3.22	3.22
40	*18*	5.07	2.34	NA	3.22	3.22
54	*4*	6.08	3.22	NA	4.00	4.00
54	*18*	6.08	3.22	NA	4.00	4.00

Panel B: Welfare Change of Manuf. Workers

		Bechmark	Unobserved Hetero.		Unobserved Hetero. 2	
Age	***Sec. Exp***	***All***	***type I***	***type II***	***type A***	***type B***
26	*4*	6,528	6,361	8,116	5,483	5,901
40	*4*	6,659	6,457	7,823	4,671	4,970
40	*18*	10,908	11,060	11,760	9,241	9,545
54	*4*	4,271	4,056	4,578	3,414	3,498
54	*18*	6,743	6,667	7,009	5,911	6,027

Panel C: Welfare Change of Metal Workers

		Bechmark	Unobserved Hetero.		Unobserved Hetero. 2	
Age	***Sec. Exp***	***All***	***type I***	***type II***	***type A***	***type B***
26	*4*	-49,023	-51,314	-77,208	-45,077	-44,214
40	*4*	-65,082	-62,288	-84,365	-55,249	-54,620
40	*18*	-88,979	-86,307	-109,768	-82,806	-82,011
54	*4*	-46,881	-44,343	-51,641	-42,134	-42,048
54	*18*	-58,879	-57,736	-64,875	-55,582	-55,495

ers would be affected since output of metal sector is not consumed but used as input in "manufacturing" and "metal" sectors.

(4) "Metal" workers would be worse off in general. However, young workers would be much less compared to middle-aged, due to their ability to move to other sectors (hence high option values). On the other hand, "Manufacturing" workers would be better off. Again young workers much less compared to middle-aged because of the drop in their option values. The relevant figures display a mirror effect in "manufacturing" and "metal" sectors.

(5) As workers get close to retirement they should be unanimous since they have less time to enjoy or suffer from the effects of free trade on their wages. To analyze effects of trade shocks on very old workers, a more detailed modelling of savings and retirement benefits is required, which is left for future research.

Appendix A: Alternative Estimations

To analyze robustness of our results we have experimented with alternative specifications. Presentation of results and discussions are kept short to limit length of the paper.

Unobserved Heterogeneity 2

We experimented with another unobserved heterogeneity specification, where a certain fraction of workers receive higher returns when they work in the manufacturing sector. This specification is rudimental and our goal is just to show how unobserved heterogeneity in wage offers might affect moving costs. We assume that a certain type of workers (type B) receive 1.5 percent higher returns than others (type A), if they work in manufacturing sector. The new human capital equation is:

$$\log h_t^{ni} = \phi_0^i + \phi_1^i Coll^n + \phi_2^i SecEx_t^{ni} + \phi_3^i MktEx_t^n + \phi_4 Coll^n SecEx_t^{ni} ... \\ + \phi_5 Coll^n MktEx_t^n + \phi_6^i typeB + z_t^{ni},$$

where ϕ_6^i is the extra sector-specific human capital of type B workers, which is assumed to be $\phi_6^1 = 0.015$ and $\phi_6^i = 0$ for $i = 2, 3, 4$. The ratio of type B workers are α, however we were not able to identify that parameter, the estimate of α is equal to approximately 0.5 where the t-statistics is about 0.02. We find that with introduction of unobserved heterogeneity in wage offers we get smaller moving cost. See Tables and 11 for details.

Simplified Basic Model vs. Restricted Utility Shocks

In the labor literature utility shocks are not common; in similar discrete choice models, such as Keane and Wolpin (1997), labor allocations are mainly driven by wages shocks. To demonstrate the effect of inclusion of utility shocks we introduce a descriptive model with a very simple moving cost and human capital structure:

$$\begin{aligned} C_t^{nij} &= C_1 + C_2^j, \\ \log h_t^{ni} &= \phi_0^i + \phi_1 Coll^n + \phi_2 SecEx_t^{ni} + \phi_3 MktEx_t^n + z_t^{ni}, \end{aligned}$$

we estimate this model using only NLSY data. Then, we repeat the exercise with a restriction $\nu = 0.04$.

We do not set ν equal to zero because otherwise we need to make substantial changes in

Table 10: Estimation - Moving Cost (Unobserved Heterogeneity 2).

Panel A: Idiosyncratic Shock Parameter

		Coefficient	*t-stat*
	ν	1.05	13.76

Panel B: Age specific cost

Parameter	*Age*	*Coefficient*	*t-stat*
C_1^1	**Age 26**	3.14	13.90
C_1^2	**Age 33**	3.34	12.99
C_1^3	**Age 40**	3.22	9.85
C_1^4	**Age 47**	3.38	9.80
C_1^5	**Age 54**	4.00	9.83

Panel C: Additional sector specific cost

Parameter	*Sector*	*Coefficient*	*t-stat*
C_2^1	**Manuf**	0.00	N/A
C_2^2	**Metal**	2.32	11.62
C_2^3	**Service**	-1.06	-11.40
C_2^4	**Trade**	-0.61	-9.56

Panel D: Additional education specific cost

Parameter	*Education*	*Coefficient*	*t-stat*
C_4	**College**	0.20	3.82

Table 11: Estimation - Human Capital (Unobserved Heterogeneity 2).

Panel A: Std. Dev. Of Wage Shock

	Coefficient	*t-stat*
σ_z	0.411	319.86

Panel B: Education Parameters

Parameter	*Sectors*	*Coefficient*	*t-stat*
ϕ_1^1	**Manuf**	0.147	10.45
ϕ_1^2	**Metal**	0.088	3.89
ϕ_1^3	**Service**	0.201	14.19
ϕ_1^4	**Trade**	0.171	12.60

Panel C: Sectoral Experience Parameters

Parameter	*Sectors*	*Coefficient*	*t-stat*
ϕ_2^1	**Manuf**	0.027	17.15
ϕ_2^2	**Metal**	0.014	3.56
ϕ_2^3	**Service**	0.030	23.14
ϕ_2^4	**Trade**	0.039	21.29
	Education	*Coefficient*	*t-stat*
ϕ_4	**College**	-0.009	-6.01

Panel D: Market Experience Parameters

Parameter	*Sectors*	Coefficient	*t-stat*
ϕ_3^1	**Manuf**	0.004	2.60
ϕ_3^2	**Metal**	0.010	3.83
ϕ_3^3	**Service**	0.005	4.18
ϕ_3^4	**Trade**	0.000	0.00
	Education	Coefficient	*t-stat*
ϕ_5	**College**	0.011	5.75

Panel E: Types

Parameter	*Coefficient*	*t-stat*
α	0.477	0.023
ϕ_6^1	0.015	NA

Table 12: Simplified Basic Model and Restricted Utility Shocks.

Panel A: Basic Model Estimates with NLSY

	ν	C_1	C_2^1	C_2^2	C_2^3	C_2^4
Coef.	1.77	5.53	0.00	3.79	-1.85	-0.40
tstat	10.34	9.78	N/A	8.37	-6.92	-2.25
	σ_z	*Sec. Exp.*	*Mkt. Exp.*	*College*		
Coef.	0.41	0.03	0.01	0.22		
tstat	321.89	41.06	11.89	61.91		

Panel B: Estimates with NLSY (Restricted Nu)

	ν	C_1	C_2^1	C_2^2	C_2^3	C_2^4
Coef.	0.04	0.34	0.00	0.39	-0.11	-0.20
tstat	N/A	76.02	N/A	50.32	-15.49	-33.42
	σ_z	*Sec. Exp.*	*Mkt. Exp.*	*College*		
Coef.	0.39	0.01	0.04	0.15		
tstat	372.04	57.36	147.22	58.99		

the computations. The results are shown in Table 12, Panels A and B respectively. Here, we show the contribution of utility shocks to large moving costs. Wage shocks can be easily identified since wages are observed. We observe that wages do not fluctuate much, but workers change sectors very often, which implies very small moving costs when preference shocks are omitted.

Alternative initial distributions (for the year 1983)

We have to guess the initial distribution of sectoral experience for older workers in estimation process, because we do not observe workers' sectoral experience in CPS. We iterate labor allocation equations using year 1983 wages to calibrate initial distribution of CPS workers. Then alternatively, we iterate using average wages over the CPS sample (year 1983 to 2001). Using a simplified model (introduced above) we show that the initial disribution of workers does not affect our results significantly. Results shown in Table 13 Panels A and B.

Appendix B: Key Equations

The expected utility function used in programming can be expressed as:

Table 13: Alternative Initial Distributions.

Panel A: Estimates with NLSY and CPS

	ν	C_1	C_2^1	C_2^2	C_2^3	C_2^4
Coef.	1.63	5.28	0.00	3.85	-2.22	-0.61
tstat	11.64	17.14	N/A	15.32	-14.32	-6.16
	σ_z	*Sec. Exp.*	*Mkt. Exp.*	*College*		
Coef.	0.41	0.03	0.01	0.18		
tstat	322.47	42.27	11.74	51.78		

Panel B: Estimates with NLSY and CPS (Alternative)

	ν	C_1	C_2^1	C_2^2	C_2^3	C_2^4
Coef.	1.54	4.91	0.00	3.74	-1.93	-0.63
tstat	18.42	17.73	N/A	16.52	-13.62	-6.94
	σ_z	*Sec. Exp.*	*Mkt. Exp.*	*College*		
Coef.	0.41	0.03	0.01	0.18		
tstat	323.05	41.10	13.22	52.98		

$$\begin{aligned}
\bar{V}_t^i\left(s_t^n,\xi_t,\right) &= E_{u,z}V_t^i\left(s_t^n,z_t^n,u_t^n,\xi_t\right) \\
&= E_z w_t^i\left(s_t^n,z_t^n,\xi_t\right)+E\max_j\beta\left\{V_{t+1}^j\left(\eta_{t+1}^n|s_t^n\right)-C^{i,j}\left(\eta_{t+1}^n\right)\right\}, \\
&= \tilde{w}_t^i\left(s_t,\xi_t\right)+\beta\Omega_{t+1}^i\left(s_t^n\right)+\beta E_{s,u,z}\left\{V_{t+1}^i\left(s_{t+1}^n,z_{t+1}^n,u_{t+1}^n,\xi_{t+1}\right)|s_t^n\right\}, \\
&= \tilde{w}_t^i\left(s_t,\xi_t\right)+\beta\Omega_{t+1}^i\left(s_t^n\right)+\beta E_s\int_z\left\{\bar{V}_{t+1}^i\left(s_{t+1}^n,\xi_{t+1}\right)-\bar{w}_{t+1}^i+w_{t+1}^i\left(s_{t+1}^n,z_{t+1}^n,\xi_{t+1}\right)\right\}dz \\
&= \tilde{w}_t^i\left(s_t,\xi_t\right)+\beta\Omega_{t+1}^i\left(s_t^n\right)+\beta E_s\bar{V}_{t+1}^i\left(s_{t+1}^n,\xi_{t+1}\right)
\end{aligned}$$

where $\tilde{w}_t^i\left(s_t,\xi_t\right)=E_z w_t^i\left(s_t^n,z_t^n,\xi_t\right)$.

Define

$$\tilde{V}_t^i\left(s_t^n,z_t^n\right)=w_t^i\left(s_t^n,z_t^n,\xi_t\right)+\beta\Omega_{t+1}^i\left(s_t^n\right)+\beta E_s\bar{V}_{t+1}^i\left(s_{t+1}^n,\xi_{t+1}\right)$$

gross flows from state s_t to s_{t+1} can be represented as:

$$m^{s_t s_{t+1}} = E_s \int_z \frac{\exp\left\{\left(\tilde{V}^j_{t+1}\left(s^n_{t+1}, z^n_{t+1}\right) - \tilde{V}^i_{t+1}\left(s^n_{t+1}, z^n_{t+1}\right) - C^{i,j}\left(s^n_{t+1}\right)\right)/\nu\right\}}{\sum_k \exp\left\{\left(\tilde{V}^k_{t+1}\left(s^n_{t+1}, z^n_{t+1}\right) - \tilde{V}^i_{t+1}\left(s^n_{t+1}, z^n_{t+1}\right) - C^{i,k}\left(s^n_{t+1}\right)\right)/\nu\right\}} dz,$$

if agent stays same age; or

$$m^{s_t s_{t+1}} = \frac{1}{7} E_s \int_z \frac{\exp\left\{\left(\tilde{V}^j_{t+1}\left(s^n_{t+1}, z^n_{t+1}\right) - \tilde{V}^i_{t+1}\left(s^n_{t+1}, z^n_{t+1}\right) - C^{i,j}\left(s^n_{t+1}\right)\right)/\nu\right\}}{\sum_k \exp\left\{\left(\tilde{V}^k_{t+1}\left(s^n_{t+1}, z^n_{t+1}\right) - \tilde{V}^i_{t+1}\left(s^n_{t+1}, z^n_{t+1}\right) - C^{i,k}\left(s^n_{t+1}\right)\right)/\nu\right\}} dz,$$

if agent is older at s_t.Note that s_{t+1} should have the correct sectoral experience given s_t following the process in (5). Finally the option value can be expressed as

$$\Omega(s_t) = -\nu E_s \int_z \log\left(\frac{1}{\sum_k \exp\left\{\left(\tilde{V}^k_{t+1}\left(s^n_{t+1}, z^n_{t+1}\right) - \tilde{V}^i_{t+1}\left(s^n_{t+1}, z^n_{t+1}\right) - C^{i,k}\left(s^n_{t+1}\right)\right)/\nu\right\}}\right) dz.$$

ACM present derivation of equations similar to the ones above in detail. The main difference here is having an additional non-linear shock, z_t, hence we take integrals over that shock using simulations.

Appendix C: A Brief Analysis of the Pew Survey

Pew Global Attitudes survey is consist of interviews conducted in 44 countries with 38,263 individuals in 2002. It includes approximately 100 questions on various popular issues and personal background. We are not using the survey data to estimate our main model but to estimate a simple descriptive probit model to illustrate our motivation for this research. A question on international trade points out a very interesting yet unexplored issue. The question is: "And what about the different products that are now available from different parts of the world - do you think this is a very good thing, somewhat good, somewhat bad or a very bad thing for our country?" We find that as people get older they are less likely to answer this question as "good" and "somehow good". We set up a simple probit model to demonstrate the correlation between age and probability of supporting free trade.

Consider that $A = 1$ if the individual, i, answers the question as "good" and else $A = 0$. We assume that $A = 1$ if and only if gains from trade u is greater than a certain threshold $\bar{u}$. We use a simple linear form

$$u_i = \beta_0 + \beta_1 Age_i + \beta_2 Age_i^2 + \beta_3 Age_i^3 + \beta_4 Female_i + \beta_5 Employed_i + \varepsilon_i,$$

Where ε is a iid shock, Employed is a dummy for employment status which is one for employed people and zero for unemployed, Female is a dummy variable which is one for female and zero for male, and Age means age in last birthday minus eighteen. Estimates show that probability of a person's gains from trade being larger than the threshold decrease with age (in a linear fashion). See Table 14 - Panel A for the estimates. The percentage of people from different age groups supporting free trade is reported in Panel B of Table 14.

Table 14: Pew Statistics.

Panel A: Pew Probit Results

	Coefficient	*Std. Error*
Constant	-0.298	0.021
Age	-0.008	0.003
Age^2	0.000	0.000
Age^3	0.000	0.000
Female	-0.020	0.014
Employed	0.053	0.015

Panel B: Probability of Supporting Free Trade in the Pew Sample

Age	*20's*	*30's*	*40's*	*50's*	*60's*	*70's*
Probability	0.374	0.353	0.316	0.302	0.277	0.238

Panel C: Probability of Supporting NAFTA in the GSS sample

Age	*20's*	*30's*	*40's*	*50's*	*60's*	*70's*
Probability	0.661	0.610	0.571	0.602	0.449	0.447

In addition to Pew data, General Social Survey, conducted in US starting from 1972, also has questions related to people's perception of free trade. The negative correlation between age and supporting free trade is also observed in GSS, but the evidence is not conclusive since the number of respondents to these questions in General Social Survey is much smaller compared to Pew data. For example 1348 people gave a valid response to the question: "Does America benefit from being a member of NAFTA?" the probability of answering "Yes" again, in general, decreases with age. See Table 10 - Panel C.

It should be noted that the questions asked in these surveys are very general; the answers given depend on many factors not observed from the data such as one's perception of free trade, consumption preferences, recent changes in trade policy in their countries, skill level, worker's industry, and many other things which would differ from country to country and person to person. The probit analysis and tables only show that there is, in general, a negative correlation between age and supporting free trade in most countries for most of the people. In the next section we set up a model to explain why age and gains from trade are correlated. We will show that welfare effects of trade liberalization depend on people's age, education and experience level as well as the type of liberalization.

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Figure 1: Flows Out of Sectors - Young Workers without Experience .

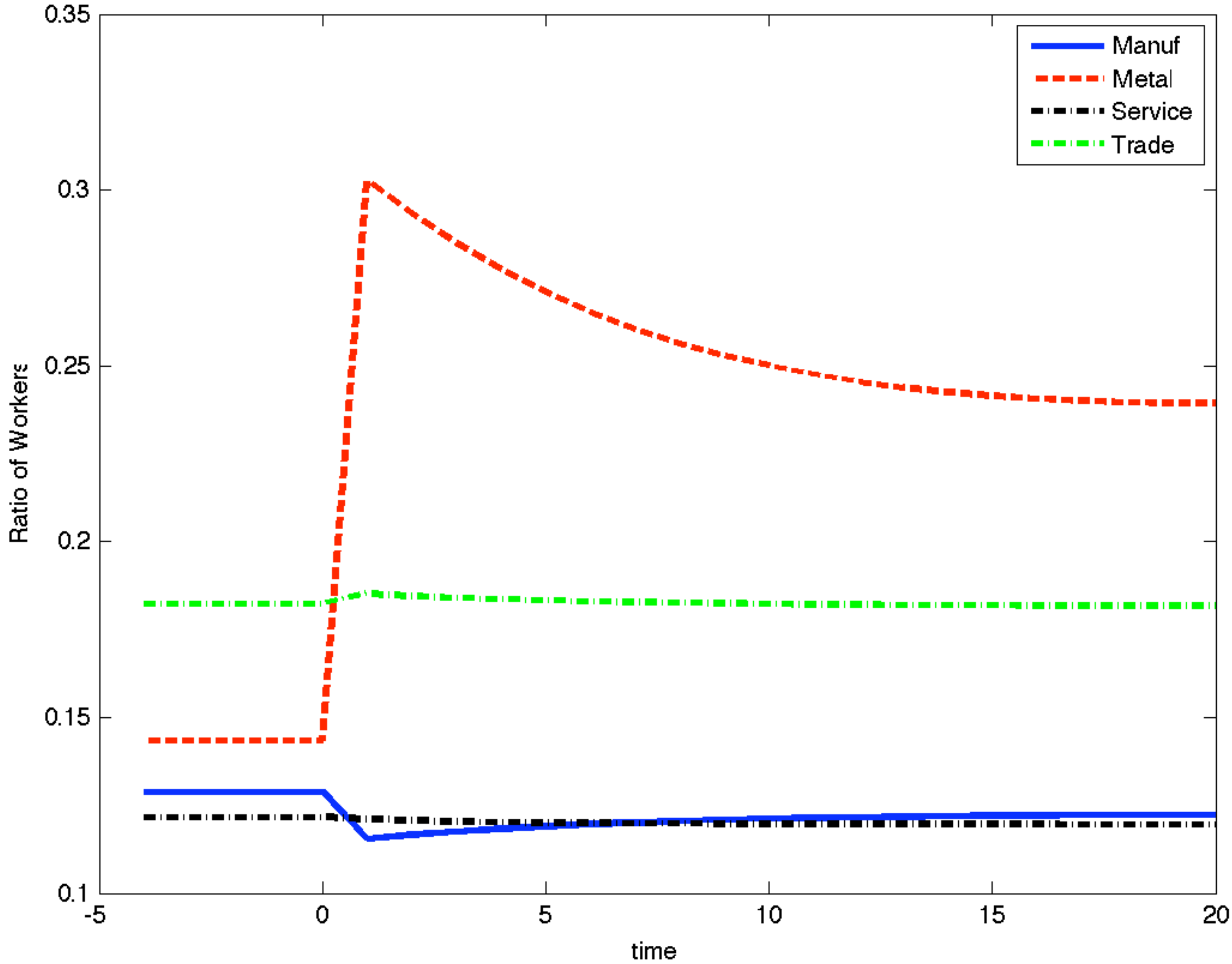
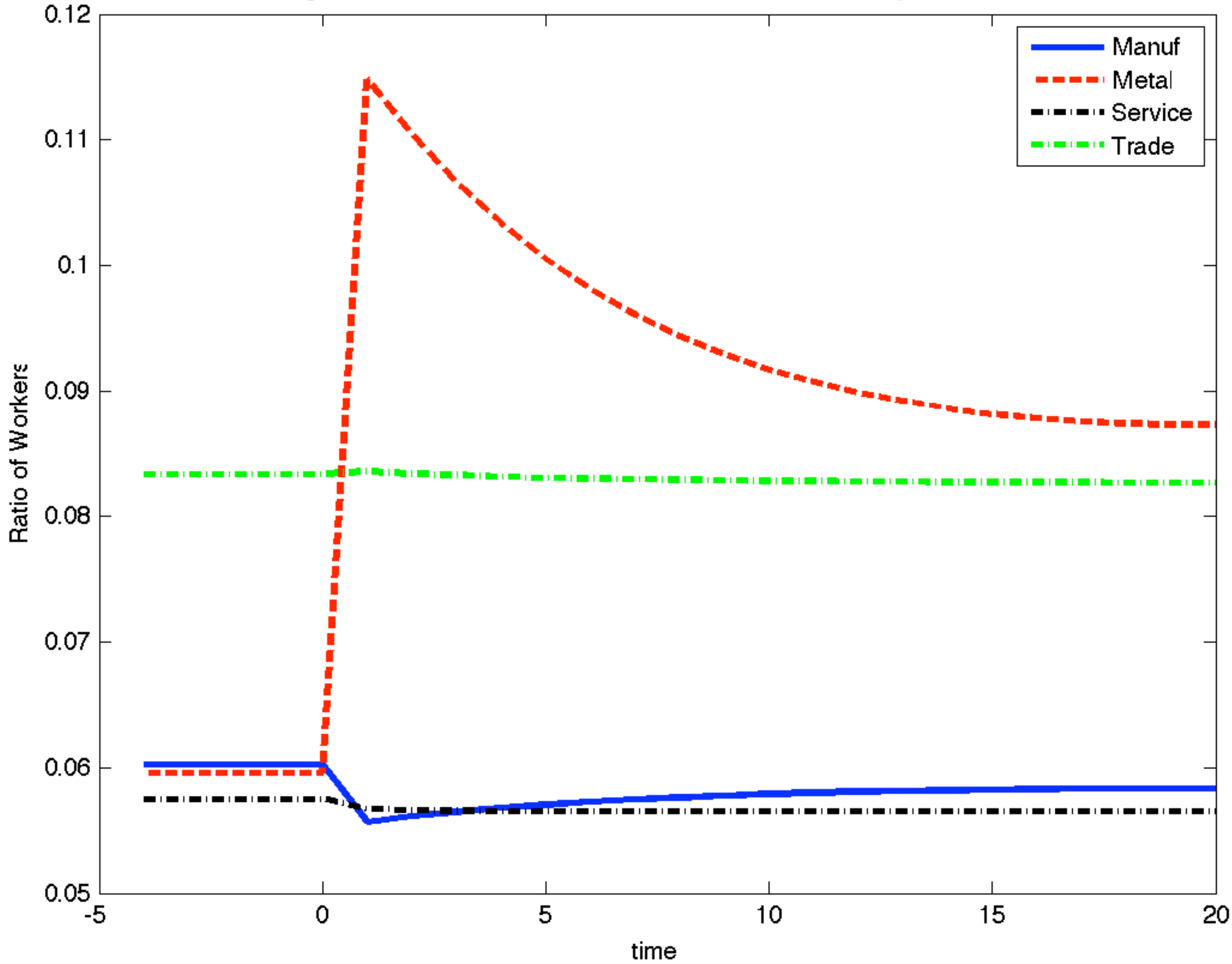


Figure 2: Flows Out of Sectors - Old Workers without Experience .



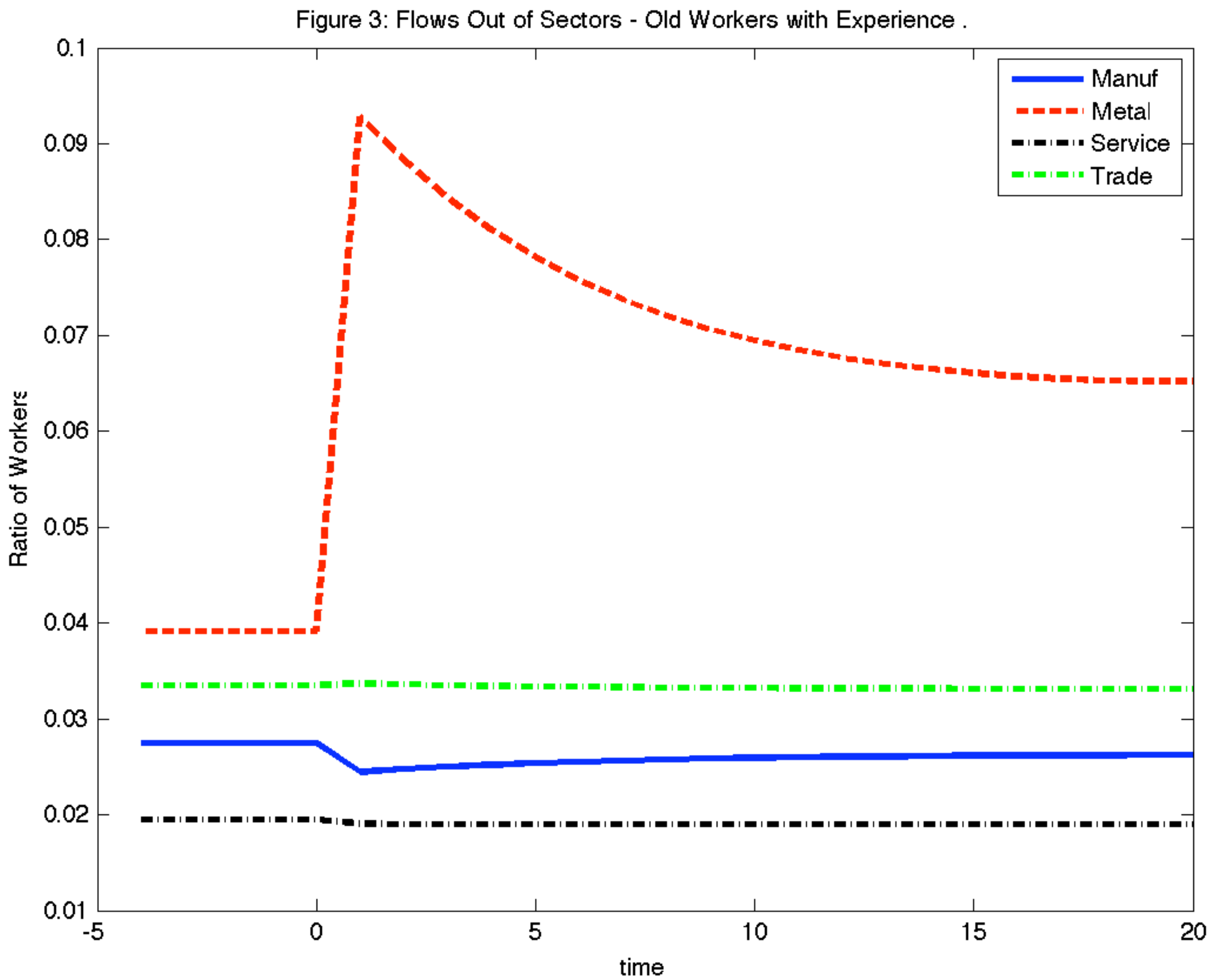


Figure 3: Flows Out of Sectors - Old Workers with Experience .
Manuf
Metal
Service
Trade
Ratio of Workers
time
0.1
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
-5
0
5
10
15
20

Figure 4: Adjustment of Wages .

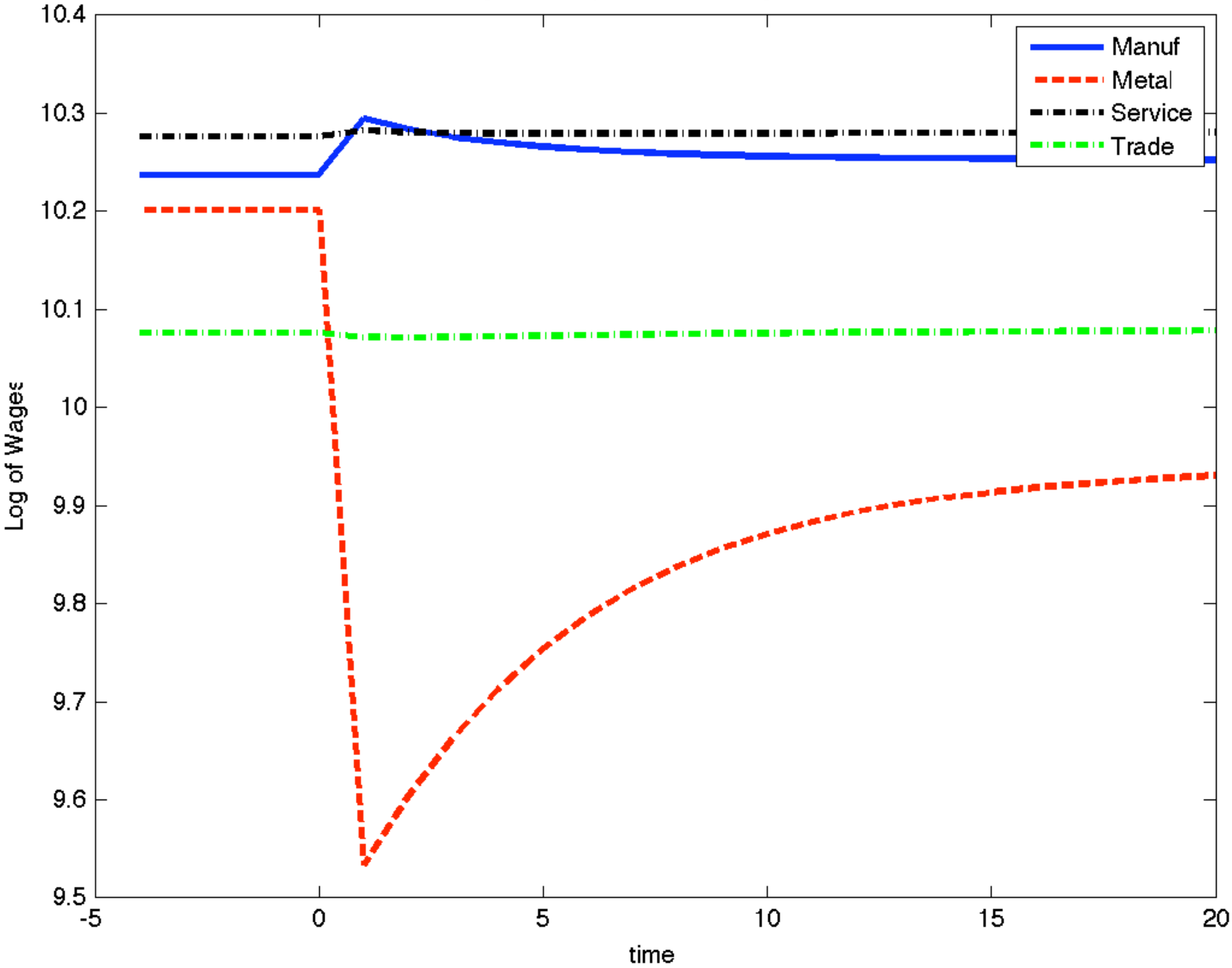


Figure 5: Percentage Change in Output .

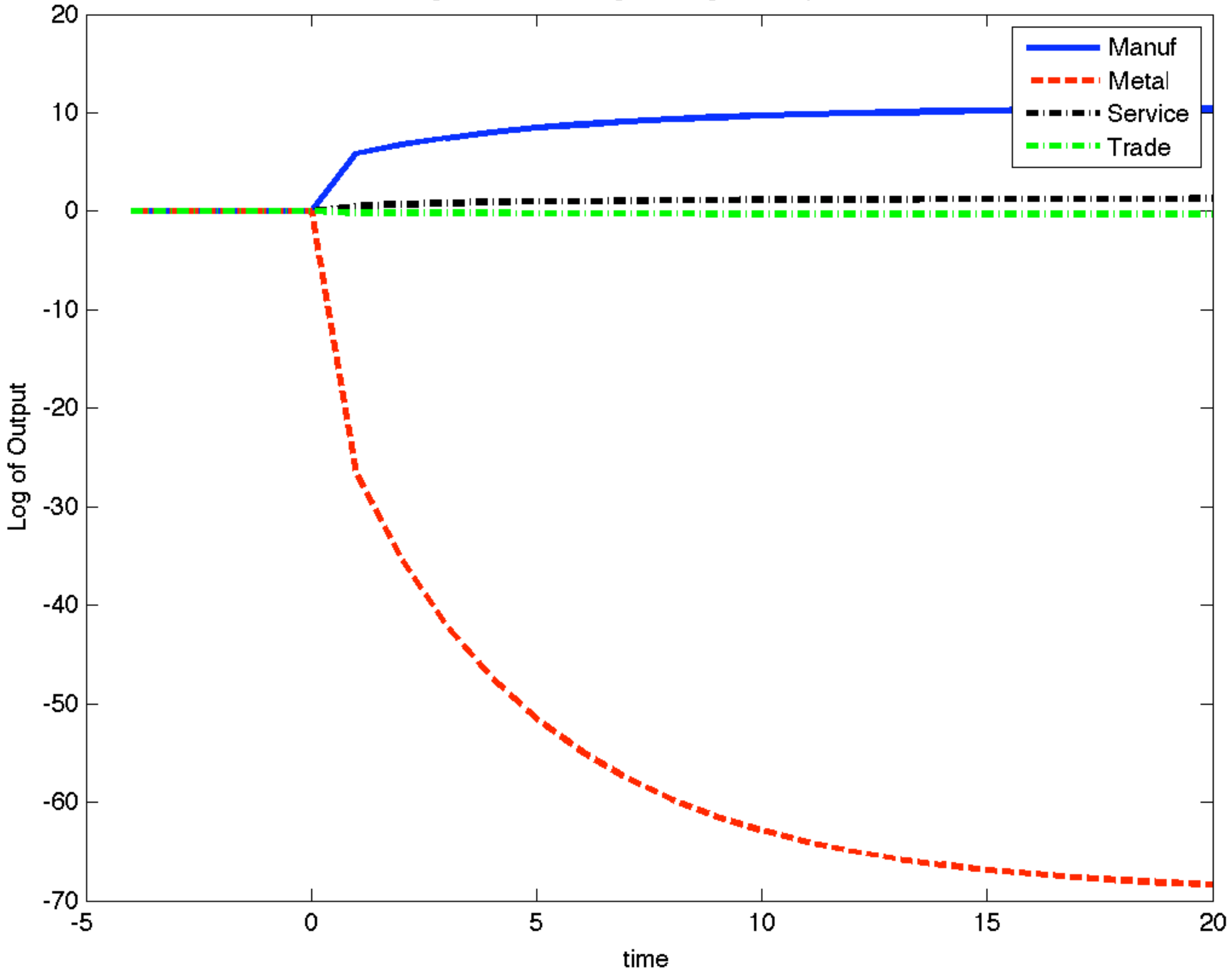


Figure 6: Percentage Change in Demand .

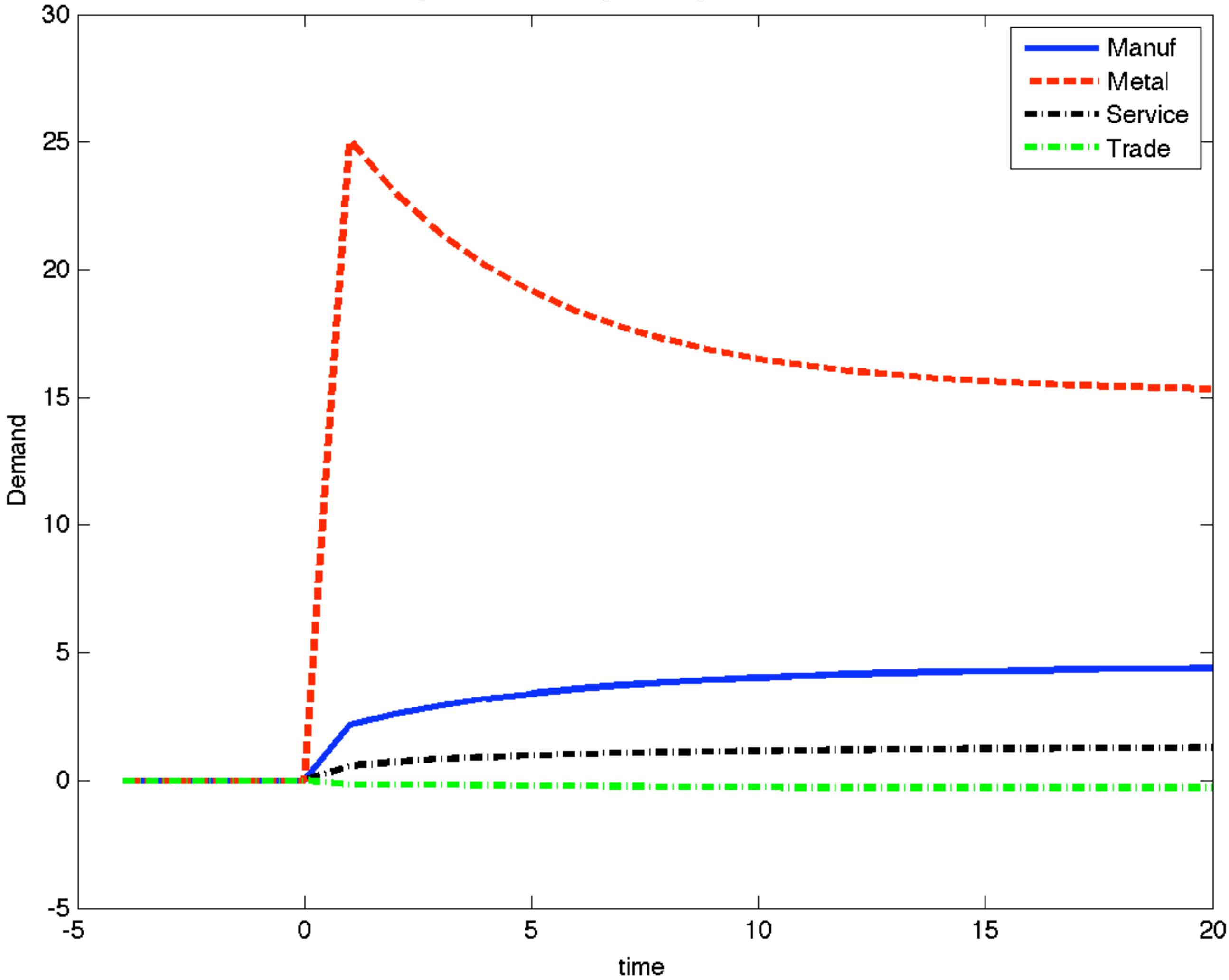


Figure 7: Percentage Change in Price .

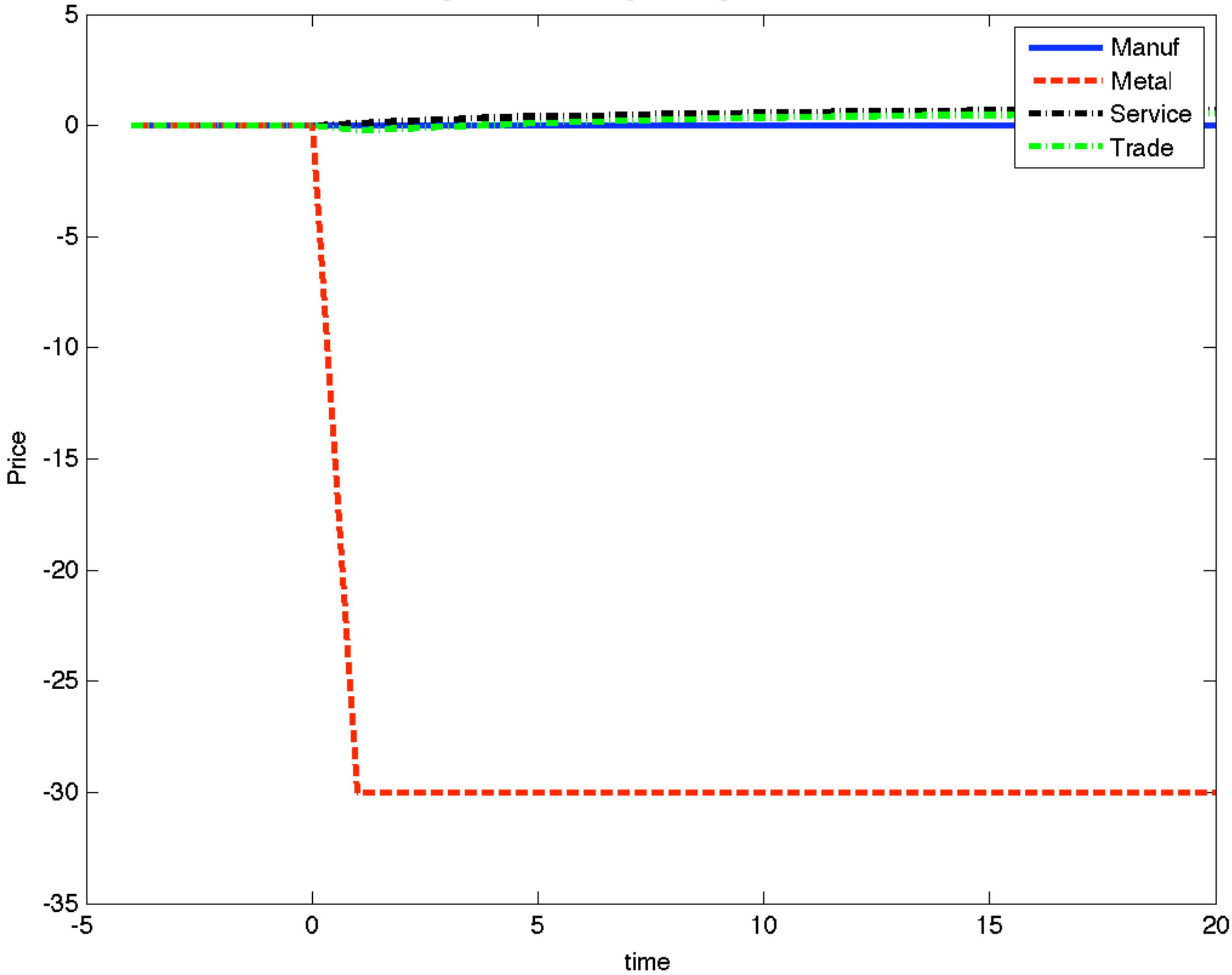
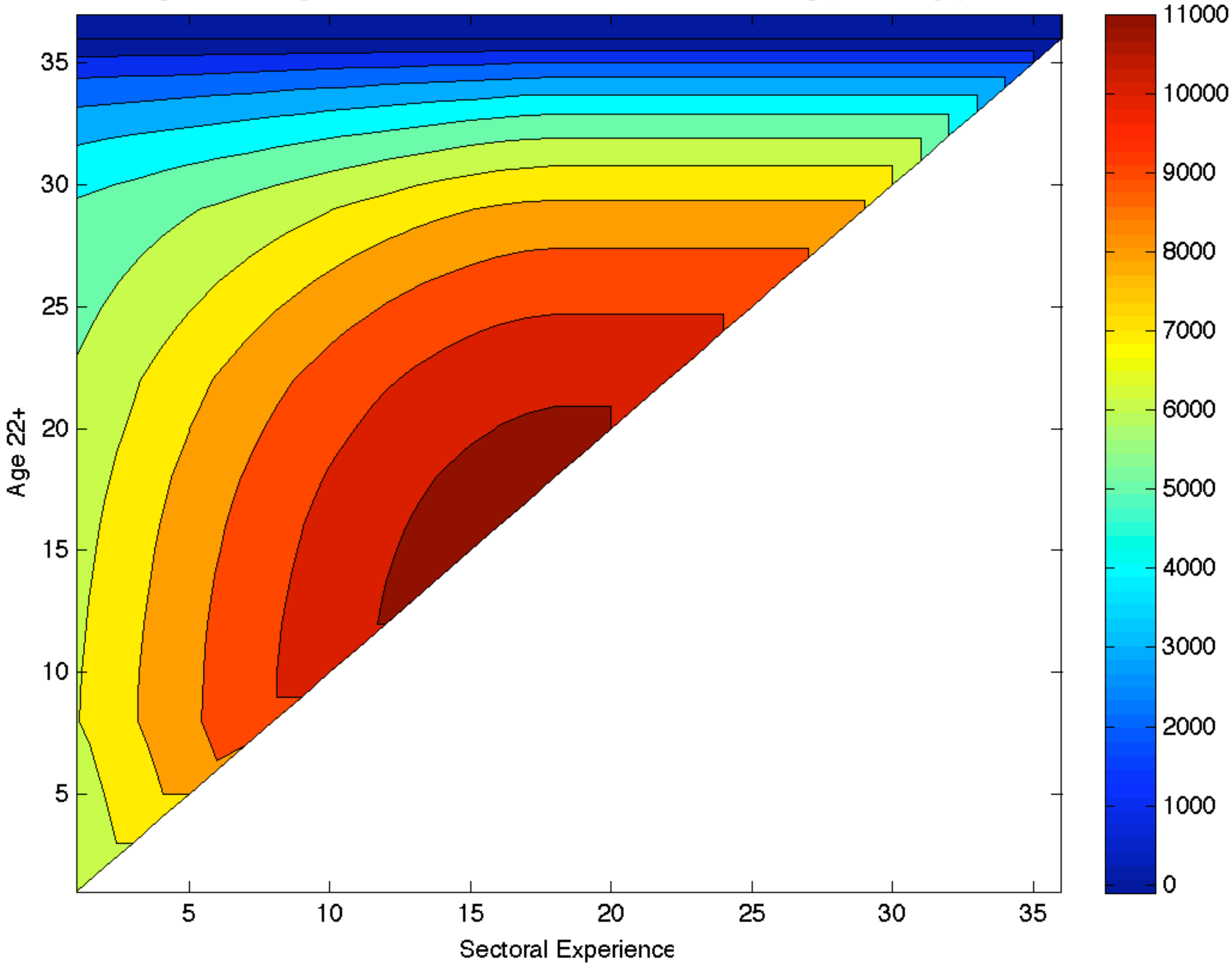


Figure 8: Change in Present Discounted Value - Manufacturing (No-College) .



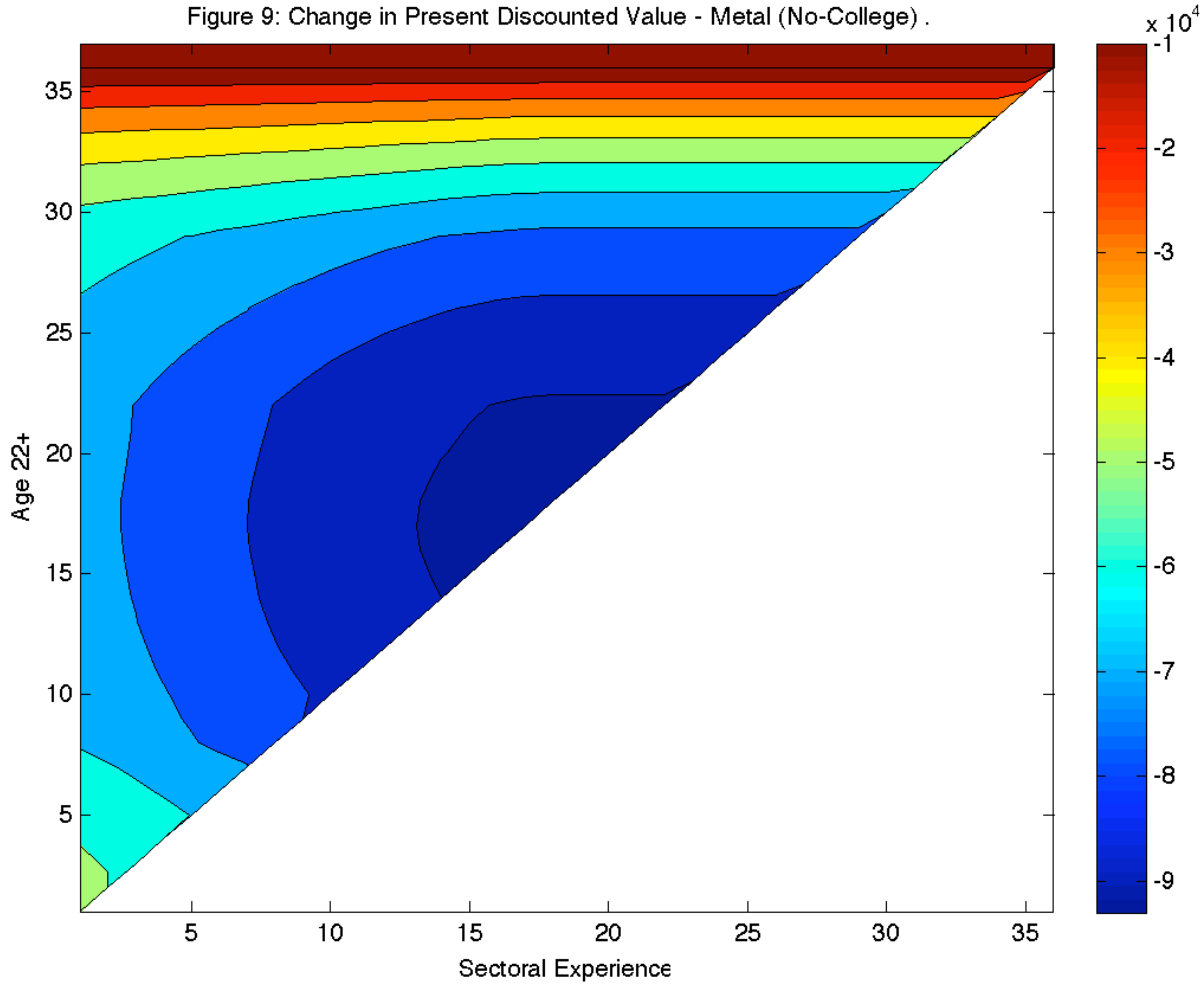


Figure 9: Change in Present Discounted Value - Metal (No-College) .
Age 22+
Sectoral Experience
x 10^4
-1
-2
-3
-4
-5
-6
-7
-8
-9
5
10
15
20
25
30
35

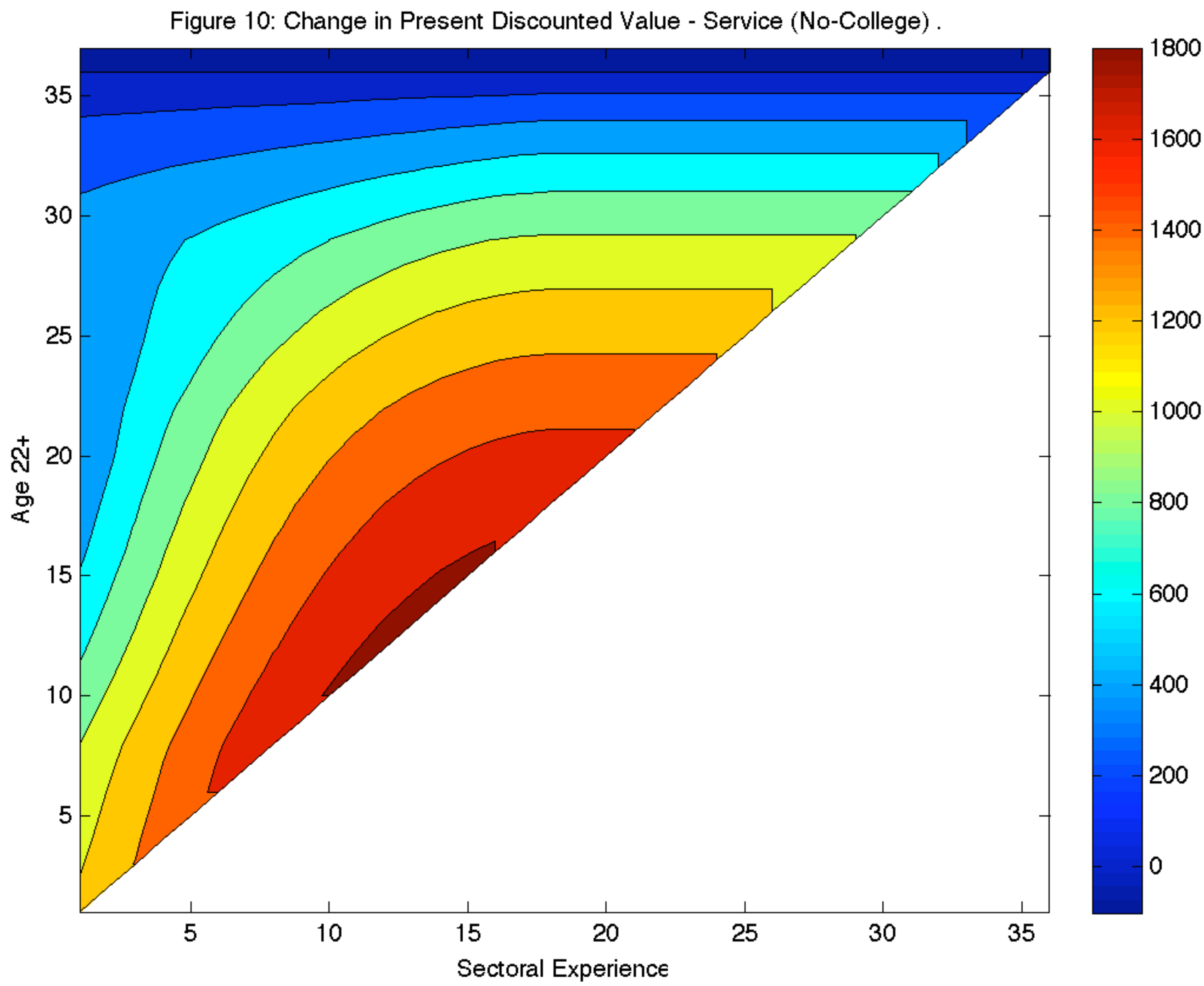


Figure 10: Change in Present Discounted Value - Service (No-College) .
Age 22+
Sectoral Experience
5
10
15
20
25
30
35
1800
1600
1400
1200
1000
800
600
400
200
0

Figure 11: Change in Present Discounted Value - Trade (No-College) .

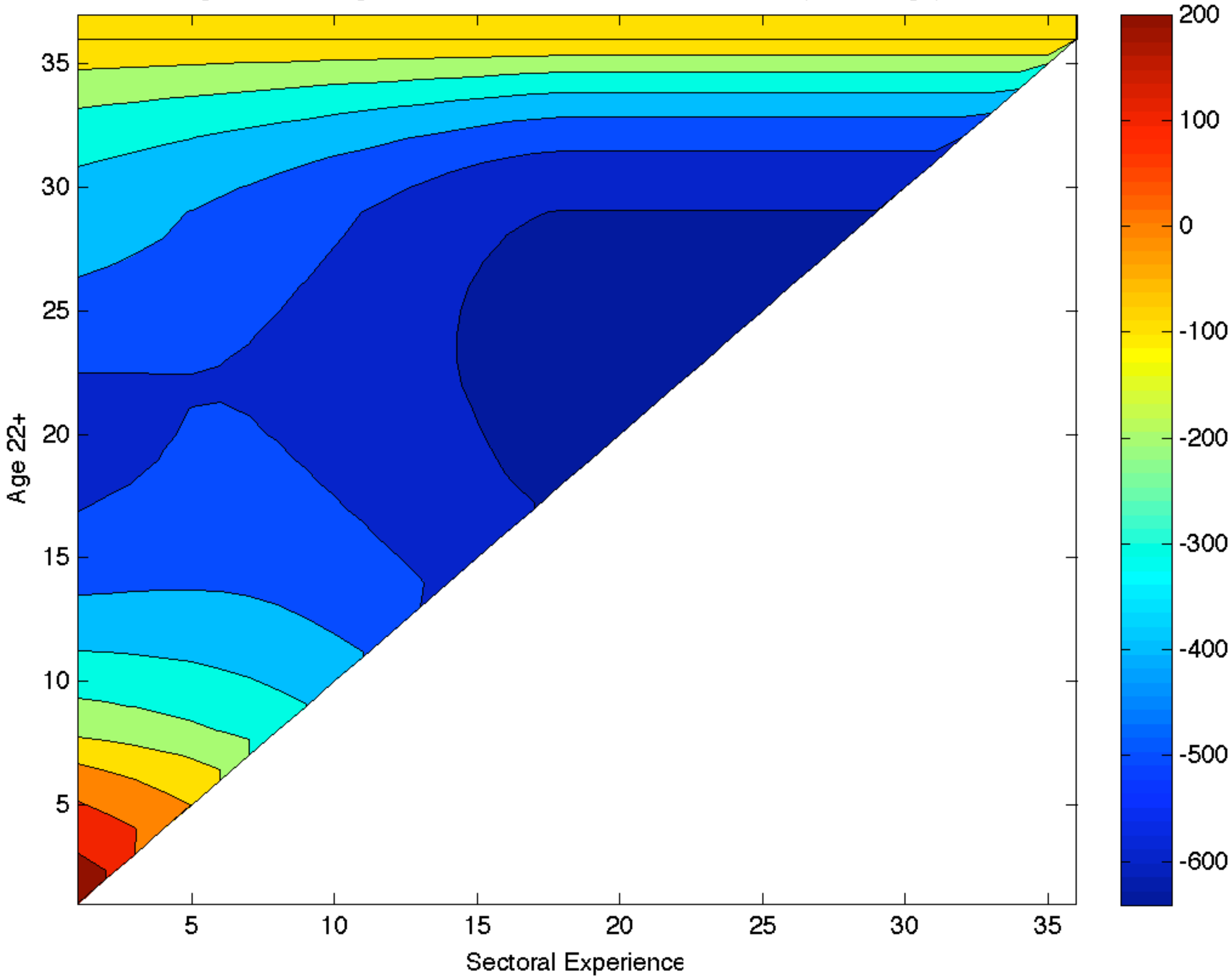


Figure 12: Change in Present Discounted Value - Manufacturing (College) .

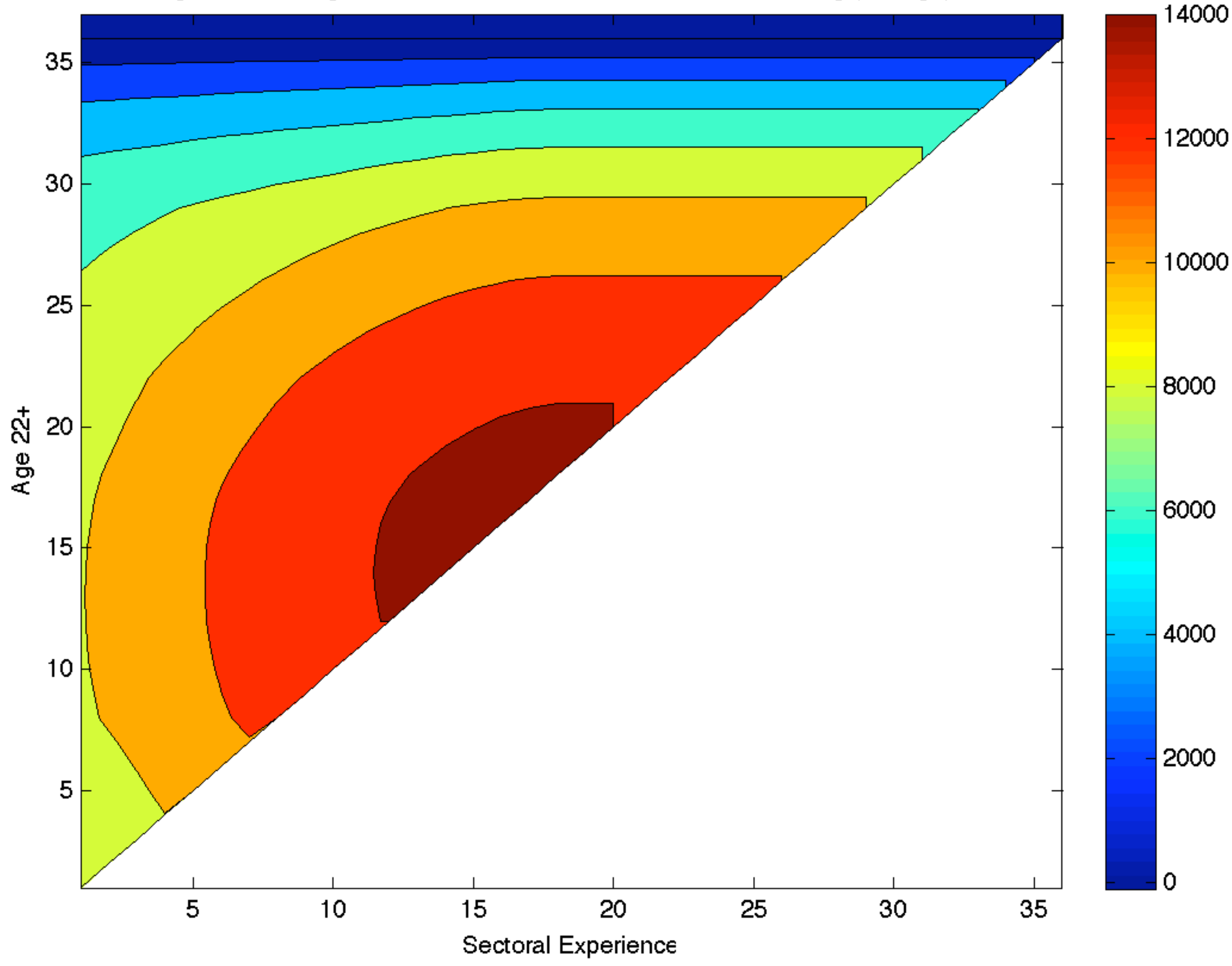


Figure 13: Change in Present Discounted Value - Metal (College) .

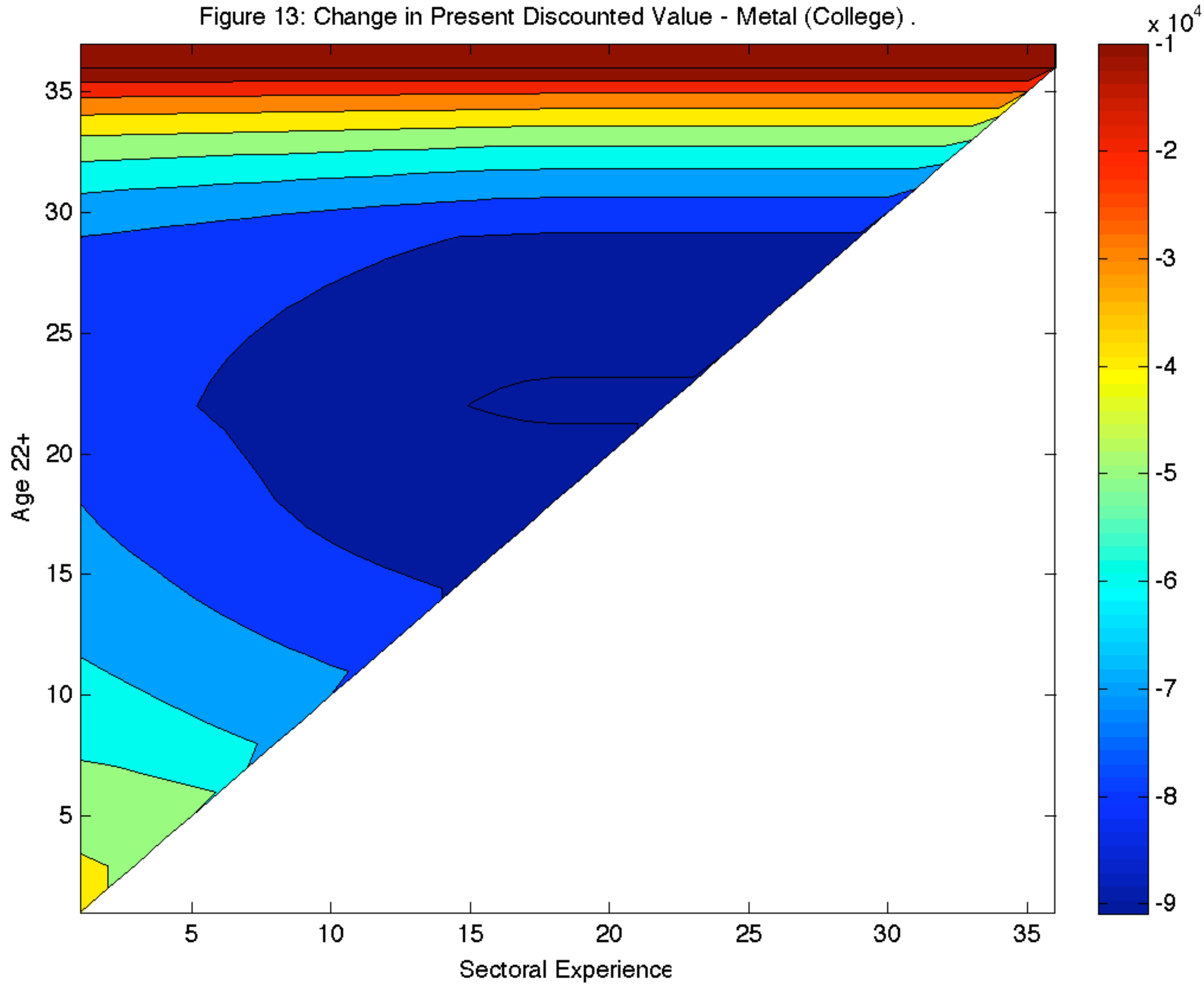


Figure 14: Change in Present Discounted Value - Service (College) .

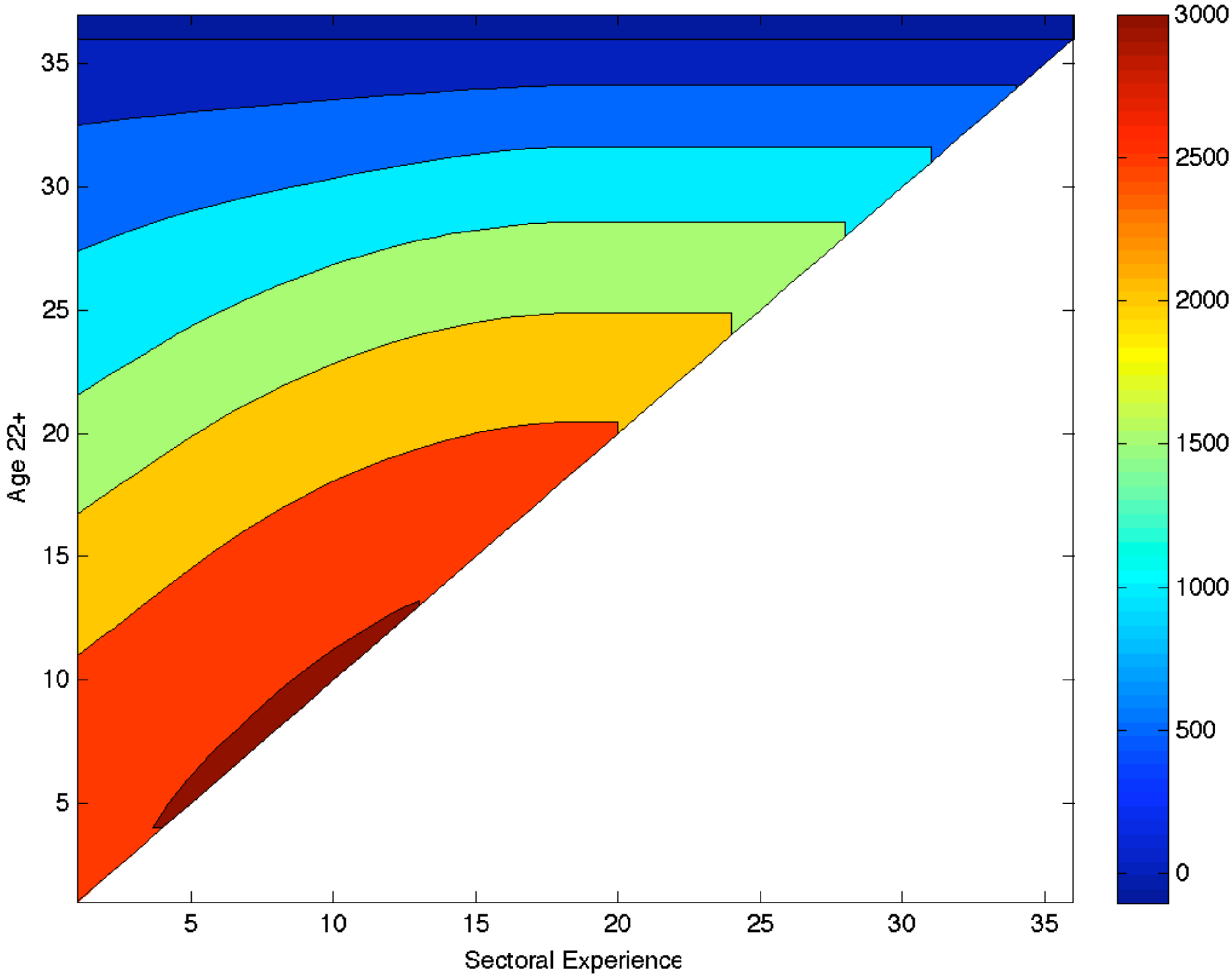


Figure 15: Change in Present Discounted Value - Trade (College) .

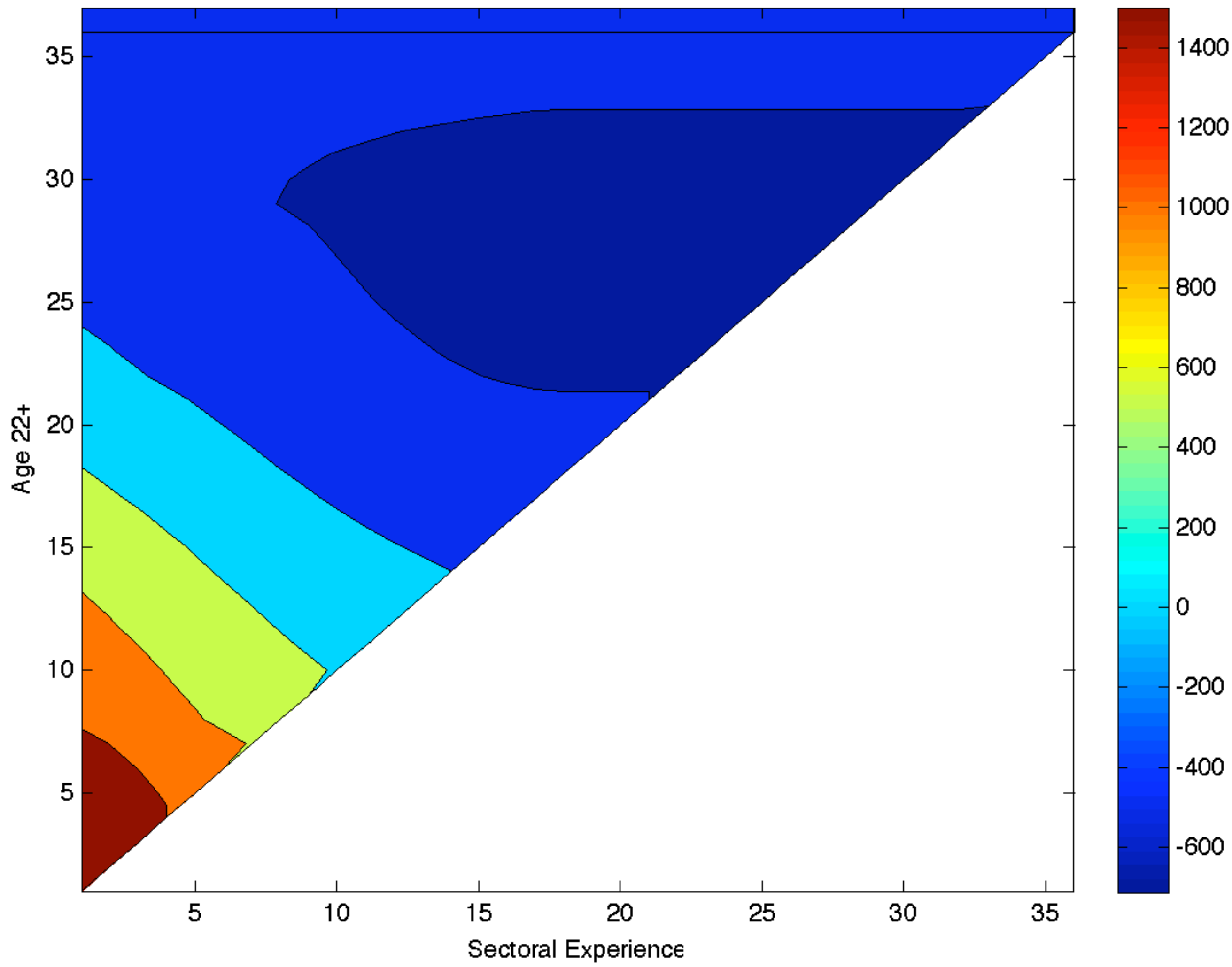


Figure 16: Actual Value Functions vs. Approximated Value Functions